ESSAYS ON BANK COMPETITION AND FINANCIAL STABILITY

A thesis submitted in partial fulfilment of the requirements for the

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Table of Contents

List of Tables

List of Figures

Abstract

The three main essays in this thesis focus on exploring the relationship between bank competition and financial stability. Chapter one gives an introduction to the literature on bank competition and stability. Chapter two addresses the question “are competitive banking systems more stable?” This chapter is a replication of the work of Schaeck, Cihak, and Wolfe (2009) and it re-analyses the authors’ original data. In addition, this chapter provides various robustness tests by comparing currently available data from the same (as the authors’) or alternative data sources and extending the sample period. In doing so, it fails to confirm Schaeck et al. (2009) conclusion that competition promotes stability.

The third and fourth chapters focus on the question: “what is the effect of bank competition on stability?” These two chapters undertake two major meta-regression analyses to identify the effect of competition on stability. The third chapter is a replication of Zigraiova and Havranek (2016). It is comprised of two validation exercises. The first is a pure replication of the authors’ analysis using their data and code. This analysis exactly reproduces the authors’ results, confirming their finding of a small effect from bank competition on financial stability. The second exercise recodes the same 31 studies using the same categories considered by the original authors. The results from the re-coded data confirm their main conclusions.

The fourth chapter updates the list of studies that estimate the relationship between bank competition and financial stability. There are a total of 35 additional studies with 762 estimates. The results using the new data confirm a small negative effect from bank competition on stability.

The fifth chapter addresses the final research question, "how does bank competition affect stability?" This chapter uses bank-level data from the USA during the period 2000-2017. It computes multiple competition and stability measures to examine how each competition measure is associated with each stability measure. The relationship between bank competition and stability is found to vary based on the measures, and estimation method, used. The results generally support the competition-fragility hypothesis, but there are exceptions, and many of the estimates are statistically insignificant.

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Chapter One

1.1 Introduction

Until the 1970s, banking sectors were generally highly regulated with tight restrictions. Banking sectors were mainly confined to a few players within the geographical boundaries of countries. There was limited competition between banks, and a minimum of bank failures. The World Bank, International Monetary Fund, the World Trade Organisation promotes financial liberalization with the aim of developing domestic financial markets, banks and accelerate the economic growth of countries (Levine, 2001). Starting in the 1980s, many countries introduced liberalization and competition to their financial systems. Financial liberalization reduced barriers to entry, allowed foreign banks to participate in domestic markets, reduced restrictions on opening branches, minimized deposit interest rate ceilings, and introduced derivative and foreign currency trading (Hellmann, Murdock, & Stiglitz, 2000). Subsequently, significant bank failures were reported in many parts of the world (Vives, 2001).

Figure 1.1 shows number of crises that started in a given year from 1970 to 2010 (reproduced from Laeven and Valencia (2012)). It shows occurrence of multiple banking crises after financial liberalization. Latin American crisis was the major crisis in 1980s. In 1990s, banking crisis in transition economies, Tequila crisis and East Asian financial crisis were the significant bank failures. Then in late 2000s, 24 countries faced the global financial crisis and it was the most impactful financial crisis after 1970.

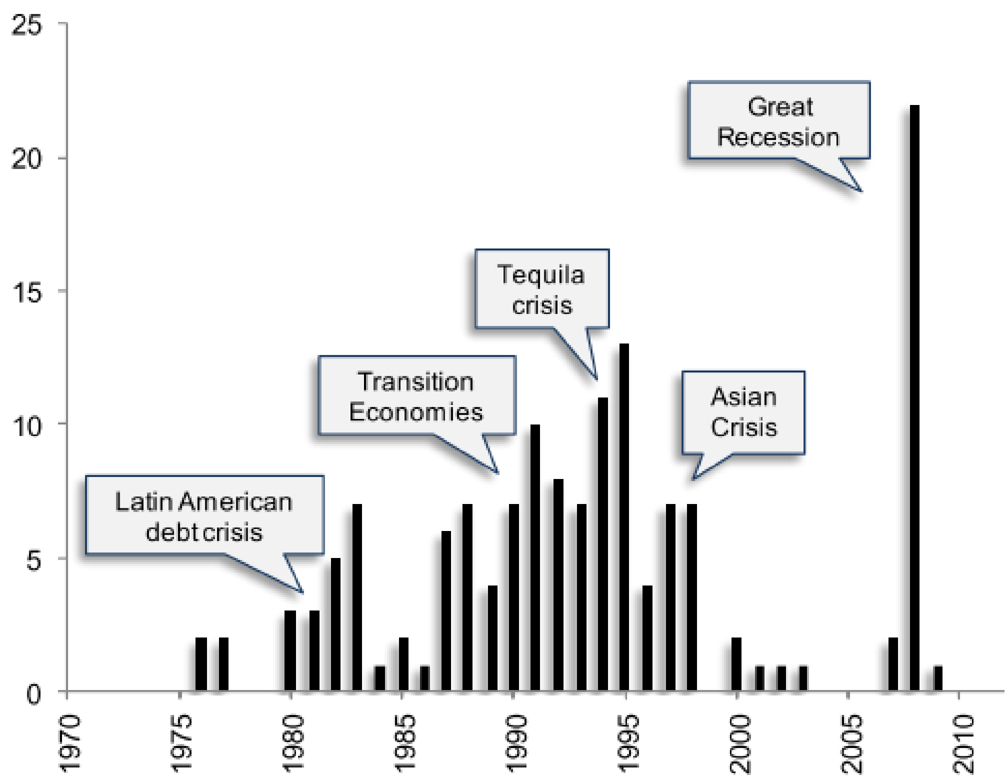


Figure 1.1: Banking Crisis Cycles
Source: Laeven and Valencia (2012)

To explain more details on banking crises in chronological order, in 1980s, the non-performing loans were estimated to be more than 30 percent of the total loan portfolios in Sub-Saharan African countries and many banks declared insolvency (Caprio & Klingebiel, 2002). Latin American countries also experienced a financial crisis in early 1980s. They had large external debt obligations and the collapse of global commodity prices combined with high and volatile interest rates in USA, contributed to banking and sovereign debt crises in Latin America (Reinhart & Rogof, 2013). USA suffered from savings and loan crisis in 1984 and more than 1000 thrift institutions failed (Curry & Shibu, 2000). In late 1980s Nordic countries experienced banking crises due to the lack of internal risk management controls and due to the absence of prudential regulatory supervision in the post-liberalization period (Drees & Pazarbasioglu, 1995).

Japanese financial system had a real estate price boom and a stock market boom in the mid 1980s and Japan had experienced a burst of asset bubbles in 1992. The decline in real estate price led to a collapse in collateral backed loans in banks. In addition to that, the decrease in stock prices reduced the value of bank's equity capital and created instability in the banking system (Bordo & Jeanne, 2002). During the same time period, Eastern European banking sector faced problems with the collapse of Soviet union (Reinhart & Rogof, 2013). Many Central and Eastern European countries and few other transition economies suffered from heavy non-performing loans they had from their socialist period. During the transition period, removal of subsidiaries for state enterprises reduced their profitability and the capacity to pay back the outstanding loans. That formed significant bank runs in many transition economies (Tang, Zoli, & Klytchnikova, 2000). Mishkin (1999) explains the financial system instability due to Tequila crisis in 1994-1995 which was created an asset and liability mismatch in bank borrowers' balance sheet. With the devaluation of the Mexican peso, dollar denominated loan values increased, while the value of domestic currency based assets did not. This resulted in defaults of loan repayments by the borrowers, which created a credit risk in the banking system. A similar phenomenon occurred in East Asian economies. Financial liberalization injected excessive foreign direct investments and during the period from 1997 to 1998, currency devaluation in many East Asian economies resulted in currency mismatches, illiquidity, and leverage issues in banks (Mulder, Perrelli, & Rocha, 2012). More recently, the falling housing prices in US initiated the sub-prime crisis in 2007. Less creditworthy borrowers defaulted their loans which led to vulnerabilities in the financial system (Reinhart & Rogoff, 2008). Later, it spread to European banks and to a global crisis (Laeven & Valencia, 2010).

Table 1.1

Global Banking Crises, 1890 – 2008

Years of bunching in banking crises	Affected countries	Comments
1890 - 1891	Argentina, Brazil, Chile, Portugal, UK, and US	Argentina defaults and there are runs on all Argentine banks (see della Paolera and Taylor (2001); Baring Brothers faces failure
1907 - 1908	Chile, Denmark, France, Italy, Japan, Mexico, Sweden, US	A fall in copper prices undermines the solvency of a trust company (quasi bank) in New York
1914	Argentina, Belgium, Brazil, France, India, Italy, Japan, Netherlands, Norway, UK, and US	The outbreak of WWI
1929 - 1931	Advanced: Belgium, Finland, France, Germany, Greece, Italy, Portugal, Spain, Sweden, US Emerging markets: Argentina, Brazil, China, India, Mexico	Real commodity prices collapse by about 51% during 1928–1931. Real interest rates reach almost 13% in the US
1981 - 1982	Emerging markets: Argentina, Chile, Colombia, Congo, Ecuador, Egypt, Ghana, Mexico, the Philippines, Turkey, and Uruguay	Between 1979 and 1982, real commodity prices fall about 40%. US real interest rates hit about 6% - their highest readings since 1933. The beginning of the decade - long debt crisis in emerging markets
1987 - 1988	Many small, mostly low-income countries, Sub-Saharan Africa particularly hard hit	The tail-end of a nearly decade-long debt crisis
1991 - 1992	Advanced: Czech Republic, Finland, Greece, Japan, Sweden Others: Algeria, Brazil, Egypt, Georgia, Hungary, Poland, Romania, Slovak Republic	Real estate and equity price bubbles in the Nordic countries and Japan burst; many transition economies cope with liberalization and stabilization
1994 - 1995	Argentina, Bolivia, Brazil, Ecuador, Mexico, and Paraguay Others: Azerbaijan, Croatia, Cameroon, Lithuania, Swaziland	The Mexican ‘‘tequila’’ crisis deals the first blow to the surge in capital inflows to emerging markets since the early 1990s

Years of bunching in banking crises	Affected countries	Comments
1997 - 1998	Asia: Hong Kong, Indonesia, Malaysia, Philippines, Taiwan, Thailand, and Vietnam Others: Colombia, Ecuador, El Salvador, Mauritius, Russia, Ukraine	The second and last blow to capital flows to emerging markets
2007 - 2008	Germany, Hungary, Iceland, Ireland, Japan, Spain, UK, US and others	The US subprime real estate bubble - and other real estate bubbles in advance economies

Source: Reinhart and Rogof (2013)

Reinhart and Rogof (2013) also present at the history of global banking crises from 1890 to 2008. Table 1.1 reproduce the same table from Reinhart and Rogof (2013). This table emphasize that countries experienced a crisis events as a group and there is a contagion effect of banking crisis to other countries (refer Table 1.1).

The academic literature investigates the relationship between financial liberalization and banking crises and present mixed evidence towards the effect financial liberalization (Angkinand, Sawangngoenyuang, & Wihlborg, 2010; Cubillas & González, 2014; Demirgüç-Kunt & Detragiache, 1998; Kaminsky & Reinhart, 1999; Minsky, 1992; Noy, 2004). According to Kaminsky and Reinhart (1999), the majority of historical crises are related to financial liberalization. In a liberalized financial system, bank managers are allowed to undertake flexible business operations. They are eager to invest in risky assets to get high returns, which leads to increased indebtedness (Minsky, 1992). In another perspective, Noy (2004) explains that financial liberalization will contribute to a banking crisis as a result of inefficient regulatory supervision. Angkinand et al. (2010); Laeven and Valencia (2010) also confirm the importance of effective regulatory supervision in a liberalized financial system. In a counter argument, financial liberalization reduces the entry barriers and promotes competition in the banking systems. Competition brings numerous benefits to the banking sector. The pressure of competitiveness brings innovation, resource allocation efficiency, and improvements in productivity (Berger & Humphrey, 1997; Ranciere, Tornell, & Westermann, 2006). Demirgüç-Kunt and Detragiache (2005) argue that liberalization is not inherently good or bad, but depends on the macroeconomic environment. In an unfavourable macroeconomic environment, competition can cause financial instability (Demirgüç-Kunt & Detragiache, 1998). Noy (2004) finds that an increase in competition would reduce the monopoly power and decrease the profit margins of existing banks making them more unstable. In another yet similar perspective, Hellmann et al. (2000) find that competition leads to deterioration of the prudent banking business in the presence of moral hazard leading to excessive risk taking. Due to this, researchers and policy makers moved to another direction of investigation which is to observe the connection between bank competition and financial system stability.

However, to analyse this phenomenon there needs to be a reliable measurement of competition which does not exist. Measures of competition have evolved over time. In the early 1990s, empirical researchers used structural measures of competition. Structural measures mainly relate to the structure-conduct-performance (SCP) hypothesis (Berger, Demirgüç-Kunt, Levine, & Haubrich, 2004). Based on the SCP hypothesis, concentration is considered as the "structure" and the "conduct" is competition. Greater concentration is accompanied by a decrease in competition (Bikker & Haaf, 2002b). Concentration is commonly measured using the concentration ratio and/or the Herfindahl-Hirschman Index (HHI).

Later, researchers argued that concentration is inappropriate for measuring the degree of competition. If market competition leads a bank to exit due to a failure or a merger, then it increases the concentration ratio. In such circumstances, a high concentration ratio can give a misleading impression of less competition in the market (Beck, 2008; Bikker & Haaf, 2002b; Claessens & Laeven, 2004; Schaeck et al., 2009). Subsequently, non-structural measures were introduced to assess competition. The Lerner index, H-statistic, and the Boone indicator are the most prominent, non-structural measures of competition[1].

[1] For a detail discussion of non-structural measures, see Chapter five.

According to the World Bank, financial stability is the absence of bank runs, hyperinflation or a crash in stock markets (The World Bank, 2016). Stability is specifically about the strength of the financial system to handle adverse shocks. Laeven and Valencia (2012) collect data on financial crises from 1970-2011 and identify 147 banking crises events. A banking crisis is considered as "systemic" when there are significant signs of financial distress in the financial system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations) accompanied by significant intervention measures (Laeven & Valencia, 2008). The interconnectedness of the financial system raises the possibility that banking crises can spill over to other components of the financial system. As a result, banking crises often occur simultaneously with sovereign debt or currency crises (Laeven & Valencia, 2012).

In the literature, the impact of crises are identified as a decline in output growth, a decline in investments, an increase in debt, or an increase in fiscal cost (Hutchison & Noy, 2005; Joyce & Nabar, 2009; Laeven & Valencia, 2012). It is generally agreed that banking crises generate a more severe impact on economic growth than currency or debt crises (Cerra & Saxena, 2008). Banking crises account for a loss of annual growth of approximately 3 to 3.5 percent of GDP. In addition to that, banking crises associated with currency or debt crises slow down economic growth and change the scope of future development prospects (Demirgüç-Kunt & Detragiache, 2005). The combined effect of banking and currency crises can account for up to 13 to 18 percent of GDP.

On average, the duration of banking crises or twin crises is within the range of 3 to 4 years (Hutchison & Noy, 2005; Laeven & Valencia, 2012). The results of Laeven and Valencia (2012) find that on average, the output loss is 33 percent of GDP and the increase in public debt is 21 percent of GDP in advanced economies[2] (Laeven & Valencia, 2012). The severity of the crisis in advanced economies depends on the interconnectedness of financial institutions (Cerra & Saxena, 2008). Given the economic significance of banking crises, regulators and policy-makers have questioned whether more (or less) competition in the banking sector would be desirable.

Theoretical views on bank competition and stability differ. The competition-fragility hypothesis holds that an increase in competition leads to a decline in bank profits. As a consequence, banks' risk preferences increase to the point where they do not sufficiently safeguard themselves (Allen & Gale, 2004; Keeley, 1990; Marcus, 1984). In contrast, the competition-stability hypothesis argues that competition promotes financial stability. When there are a few large banks, the operations of banks are very complex and more difficult to supervise. Further, they receive “too-big-to-fail” subsidies from the regulatory authorities. This encourages risk-taking behaviour. On the flip side, competition in lending results in lower interest rates charged on loans. Low interest rates attract low-risk taking borrowers and reduce the amount of non-performing loans. There are less adverse selection and moral hazard issues in competitive banking systems. Together, these arguments support the competition-stability hypothesis (Boyd & De Nicolo, 2005; Boyd, De Nicolo, & Jalal, 2006; Jiang, Levine, & Lin, 2017; Schaeck & Cihak, 2014; Schaeck et al., 2009).

1.2 Research Questions

The aim of this thesis is to investigate the relationship between bank competition and financial stability. This broader research aim is narrowed down to three specific research

[2] Based on World Economic Outlook country categorization
https://www.imf.org/external/pubs/ft/weo/2015/02/weodata/groups.htm#cc

questions. The first question is "are competitive banking systems really more stable?" The competition-stability hypothesis predicts a positive relationship between bank competition and stability. This thesis addresses this question by performing a replication of a study that finds more competitive banks are less likely to experience systemic crises (Schaeck et al., 2009). The second question is "what is the effect of bank competition on stability?" Meta-analysis is used to aggregate the results from the empirical literature to come up with an overall estimate of the effect of bank competition on stability. The final question is "how does bank competition affect stability?" The question is addressed using bank-level data from the US for the period 2000-2017.

1.3 Structure of the Thesis

Chapter two replicates the work of Schaeck et al. (2009) titled "Are Competitive Banking Systems More Stable?" The replication begins by reproducing key findings using the authors' data and code. It then updates the control variables of the study with currently available data from the same and alternative data sources. The analysis then extends the sample period to 1980-2011 (from 1980-2005) and re-estimates the key models. Finally, alternative measures of competition and financial stability are used to see whether the conclusions of Schaeck et al. (2009) are robust to these changes.

The literature gives conflicting results about the relationship between bank competition and financial stability. Zigraiova and Havranek (2016) do a meta-regression analysis (MRA) to collect empirical results from the literature on competition and stability. When the different estimates are aggregated and analysed, they find an overall negative but small effect of competition on stability. Chapter three replicates Zigraiova and Havranek (2016) using their data and code, obtaining identical results. Subjectivity can play an important role in categorizing various variables. Accordingly, the chapter proceeds by re-coding the same studies as Zigraiova and Havranek (2016) to determine whether this affects the results.

Chapter four uses the same specifications as the third chapter, but applies these to a different sample of studies to estimate how bank competition effect financial stability. It collects 762 estimates from 35 studies to address the research question, “what is the effect of bank competition on stability?”

Chapter five builds on the lessons learned from chapters three and four. Those chapters found that results can vary depending on the measures used for competition and stability. Chapter five computes multiple competition and stability measures using bank-level data from the USA over the period 2000-2017. The bank-level competition measures are H-statistic, the Lerner index, and the Boone indicator. The stability measures include two types. Z-score, non-performing loans, and distance-to-default are bank-level stability measures. Logistic R-squared and the change in conditional value at risk are systemic stability measures.

The final chapter concludes by summarizing key findings from all the chapters.

1.4 Key Findings

This section presents key findings from each chapter. The replication of Schaeck et al. (2009) finds that, using the authors’ data and code, bank competition, as measured by H-statistic, is positively associated with stability. However, when the data are updated with currently available data from the same and alternative data sources, the results of Schaeck et al. (2009) cannot be reproduced. The H-statistic is always statistically insignificant at the 5 percent level. Even when the timespan is expanded to 2011, the H-statistic continues to be statistically insignificant.

As a robustness test, Chapter 2 uses Z-score as an alternative measure of stability. The effect of H-statistic on stability continues to be statistically insignificant. In addition to statistical insignificance, the estimated effects for H-statistic are small in terms of economic significance. An increase in H-statistic from its 25th to 75th percentile is associated with a reduction in the probability of systemic crisis by 0.1 percentage points. A similar change in H-statistic is associated with a reduction in the inverse probability of default (Z-score) by 0.17 percentage points. Chapter 2 includes the Lerner index and the Boone indicator as additional competition measures. Both these measures remain insignificant in the analysis.

Chapter 3 replicates Zigraiova and Havranek (2016) and finds that the pure replication results match the original results reported by the authors. The mean partial correlation between competition and stability is estimated to be insignificant in both statistical and economic terms. Chapter 3 recodes the same 31 studies used by Zigraiova and Havranek (2016), using the same study and data characteristics, to see if subjectivity in coding produces different results. While the results are not identical, the overall conclusion is the same.

Chapter 4 repeats the analysis by collecting a new sample of more recent studies on banking competition and financial stability. It analyses 35 additional studies, with 762 additional estimates. The results are largely the same as Zigraiova and Havranek (2016) with respect to the estimated relationship between competition and stability. Chapters 3 and 4 also find that there are systematic differences in estimated competition effects depending on the specific measures used for competition and stability.

The results of chapter five confirm the findings of the previous two chapters. It finds that the relationship between bank competition and stability varies depending on the competition and stability measures used. When Z-score is used to measure stability, all the competition measures are estimated to be negatively associated with stability. A similar relationship is observed when distance-to-default is used to measure stability. However, the results are not statistically significant. Somewhat different results obtain when non-performing loans are used to measure financial stability. In this case, the Lerner index and the Boone indicator are estimated to be positively associated with stability. Despite these differences, the associated economic significance for all the competition measures is very small. When the analysis turns to systemic stability, none of the estimated competition variables are statistically significant.

1.5 Implications and Contribution of the Research

There has been much interest among policymakers and researchers as to whether bank competition influences the stability of the financial system. This thesis undertakes an extensive analysis and investigates three research questions related to this subject.

The results suggest that there is only a very small association between bank competition and financial stability. It does not find evidence to support the view that more competitive banking systems are less likely to experience crises. An implication of this finding is that the competitive structure of the banking sector does not hold the key to improving financial stability. As such, the findings from this thesis will hopefully encourage researchers to look elsewhere for other factors that hold promise for addressing this important issue.

Chapter Two

2.1 Introduction

In 2009, Klaus Schaeck, Martin Cihak, and Simon Wolfe (henceforth SCW) published a paper in the *Journal of Money, Credit, and Banking* entitled "Are Competitive Banking Systems More Stable. SCW examined the relationship between the competitive conduct of banking systems and financial stability. They estimated the relationship between the competitiveness of the banking system and the risk of a systemic crisis with the intention of providing empirical evidence for conflicting views on bank competition and financial stability. This chapter replicates SCW and examines whether competition in the banking system contributes to financial stability or instability.

The replication consists of six parts; (a) re-analysis of the data using the dataset provided by the authors of the paper, (b) updating of their dataset using multiple sources such as World Development Indicators, International Financial Statistics, Global Development Index Database, Deposit Insurance Database, Global Financial Development database, and DataMarket, (c) re-analysis with an extended sample period, (d) re-analysis using a different measure of stability, (e) re-analysis using alternative measures of bank competition, and (f) re-analysis excluding the effect of the global financial crisis (GFC). A summary of the findings follows.

SCW use Panzar and Rosse (1987) H-statistic as a measure of bank competition and find that (i) more competitive banking systems are less likely to experience a systemic crisis, and (ii) increased competition in the banking system is associated with greater stability. Findings of the replication exercise in this chapter confirm the authors' findings using their data. This chapter then proceeds by updating data from the same data sources used by SCW, as well as using other sources that provide data for the same variable. This allows making a comparison between the values of the variables and at the same time to increase the number of data points.

The updated values of data are different compared to SCW's dataset. When the data are updated with recently published data, SCW's conclusions are no longer valid and the H-statistic variable is always statistically insignificant. The associated t-statistic drops from 2 to 1 using the updated data. In contrast, the bank concentration variable confirms SCW's findings and shows that more concentration is associated with greater stability. This suggests that if SCW had conducted their analysis with more recently published data, they would not have come to the same conclusion about competition and financial stability that they presented in their paper.

The inclusion of alternative measures of competition and stability finds that the relationship between bank competition and stability varies based on the selected measure. There is no consistency in the results and all the competition measures are statistically insignificant, with the associated t-statistics substantially small (<1) in most cases. While the concentration variable confirms SCW's conclusion and is positively associated with financial stability, the results are statically insignificant in half of the regressions.

The remainder of the chapter is organized as follows: Section 2.2 explains the theoretical and empirical views on bank competition and financial stability. Section 2.3 discusses the original paper of SCW. Section 2.4 explains the econometric approach of SCW. Section 2.5 presents the replication results. Section 2.6 updates control variables from various data sources and presents regression results based on updated data. Section 2.7 re-estimates regressions using data for an extended sample period. Section 2.8 re-estimates the models using Z-score as an alternative measure of stability. Section 2.9 estimates the effect size of the H-statistic. Section 2.10 re-estimates the models using the Lerner index and Boone indicator as alternative measures of competition. Section 2.11 performs the analysis by excluding the global financial crisis episodes. Section 2.12 summarizes the conclusions.

2.2 Theoretical and Empirical Views on Bank Competition and Financial Stability

There are two opposing theoretical views on bank competition and financial stability. One view holds that more competition is associated with financial instability. The increase in competition leads to a decline in bank profits and, consequently, the bank's preference for risk increases. This makes them more vulnerable to financial shocks, which increases the risk of bank failure (Allen & Gale, 2004; Keeley, 1990; Marcus, 1984).

Boyd and De Nicolo (2005) introduce an alternative explanation for how more competition can lead to greater stability. In a less competitive banking system, failure of a large bank may easily spill over to other financial institutions, creating instability in the entire financial system. To prevent this situation, regulatory authorities implement policies to protect large banking institutions (Mishkin, 2006). However, these policies encourage risk-taking behaviour of large banks and increase the probability of failure. A similar view is provided by Caminal and Matutes (2002) who claim that there is a higher probability of bankruptcy in a monopolist environment compared to a competitive environment. Increasing competition reduces the power of individual players and thus reduces the risk of failure.

Traditionally empirical researchers have used structural measures as proxy measures of bank competition. Structural measures mainly relate to the structure-conduct-performance (SCP) paradigm (Berger et al., 2004). Based on the SCP paradigm, concentration is considered as "structure" and the "conduct" is competition. This approach measures the influence of concentrated banking structures on competitive conduct (Bikker & Haaf, 2002b). The most common measures of "structure" are concentration ratios and the Herfindahl-Hirschman Index (HHI).

More recently, researchers have argued that concentration is an inappropriate measure of competition because a high concentration ratio does not necessarily indicate a lack of competition. The concentration ratio is computed by using the market share of the largest banks, which does not indicate the competitiveness of the banks (Beck, 2008; Bikker & Haaf, 2002a; Claessens & Laeven, 2004; Schaeck & Cihak, 2014; Schaeck et al., 2009). Therefore, recent literature uses non-structural measures to gauge the competition.

The most common non-structural measures are the H-statistic, the Lerner index, and the Boone indicator (Agoraki, Delis, & Pasiouras, 2011; Anginer, Demirguc-Kunt, & Zhu, 2014; Schaeck & Cihak, 2014; Yeyati & Micco, 2007). These measures consider the reaction of banks' outputs to their inputs (Beck, 2008). There are pros and cons for each of these measures and none of them are perfect measures of competition[3].

[3] For a detail discussion of non-structural measures, see Chapter five.

2.3 Discussion of the Original Paper

Schaeck et al. (2009) has been cited 479 times in Google Scholar and 127 times in Web of Science (June 2018). It is an improved version of their International Monetary Fund working paper. SCW conduct an empirical analysis of the likelihood and timing of a banking crisis and its relationship with the competitive character of the banking system. Their study suggests that policy makers should promote competition in the banking system because there is a positive association between bank competition and financial stability. SCW's paper focuses on three main areas: Firstly, use of H-statistic developed by Panzar and Rosse (1987) as a better measurement of competition. Secondly, application of duration analysis with time-varying covariates to assess the timing of crises. And thirdly, simultaneous incorporation of the concentration ratio and the H-statistic to capture both "bank conduct" and "bank structure".

SCW's sample consists of 45 countries from 1980 to 2005 (Refer Appendix 5). The dependent variable of the study is a dummy variable that takes value "1" if a given country had experienced a systemic crisis in a particular year or "0" otherwise. The main explanatory variables are the Panzar and Rosse (1987) H-statistic and the three-bank concentration ratio. The H-statistic measures market power by the extent to which a change in input prices is reflected in the equilibrium revenues of the bank (Bikker & Haaf, 2002a). The thee-bank concentration is the proportion of assets held by the three largest banks of the country.

Additionally, SCW include control variables for growth of the gross domestic production (GDP), inflation, real interest rate, depreciation in the foreign exchange rate, terms of trade, credit growth as macroeconomic controls, and a moral hazard index to capture the increasing risk as a result of deposit insurance scheme. SCW use a set of dummy variables as controls for legal origin of countries, and regional dummies to control for different economic development in Africa, Latin America, the group of 10 (G10), and other economies. They find that more competitive banking systems are less vulnerable to a systemic crisis, and that the time to crisis increases in a competitive environment. Bank concentration also decreases the probability of a crisis and increases the time to crisis. Their results confirm that competition and concentration are different characteristics of banking system.

2.4 Econometric Approach

SCW use two estimation methods in their paper: duration models and binary choice (logit) models.

2.4.1 H-Statistic

Panzar and Rosse (1987) H-statistic is extensively used as a measure of competition in many studies: Bikker and Haaf (2002a); Bolt and Humphrey (2015); Casu and Girardone (2006); Claessens and Laeven (2004); Leon (2015); Matthews, Murinde, and Zhao (2007); Maudos and Solís (2011); Molyneux, Lloyd-Williams, and Thornton (1994); Schaeck et al. (2009); Yeyati and Micco (2007).

The H-statistic measures the extent to which input prices are incorporated in bank revenues, either from interest or from all sources (total). The H-statistic is estimated as follows:

$$ln\,(P_{it}) =$$

$$\alpha + \beta_{1i}\, ln(W_{1,it}) + \beta_{2i}\, ln(W_{2,it}) + \beta_{3i} ln(W_{3,it}) + \gamma_{1i}\, ln(Y_{1,it}) + \gamma_{2i}\, ln(Y_{2,it}) +$$

$$\gamma_{3i}\, ln(Y_{3,it}) + \delta D + \varepsilon_{it} \quad , \tag{2.1}$$

where P_{it} is the ratio of interest revenue to total assets (proxy for output price), W_1 is the ratio of interest expenses to total deposits and money market funding (as a proxy for the input price of deposits), W_2 is the ratio of personnel expenses to total assets (as a proxy for the price of labour), and W_3 is the ratio of other operating and administrative expenses to total assets (as a proxy for the price of fixed capital), with *i* denoting bank *i* and *t* denoting time *t*. Y_1 is a control variable for the ratio of equity to total assets, Y_2 controls for the ratio of net loans to total assets, and Y_3 is the log of total assets to capture size effects. *D* is a vector of year dummies for 1998–2005 (the dummy for 1998 is dropped to avoid perfect collinearity). All non-dummy variables are entered in equation (2.1) in logs. The H-statistic is calculated as $\beta_{1i} + \beta_{2i} + \beta_{3i}$ (Claessens & Laeven, 2004; Schaeck et al., 2009). The estimation method of H-statistic is diverse in the literature. Claessens and Laeven (2004); Schaeck et al. (2009) estimated the equation (2.1) using two estimation methods. They have employed OLS with time dummies and GLS with time dummies. The OLS estimation is inefficient and produces invalid standard errors when the errors are nonspherical. The common nonspherical errors are heteroscedasticity and autocorrelation. The GLS produced efficient coefficients and robust standard errors with the presence of nonspherical error structures. This chapter follows the estimation method of Schaeck et al. (2009). Olszak, S´witala, and Kowalska (2013) used random effects and fixed effects GLS and Pawlowska (2012) used fixed effects, OLS, and GMM to estimate the equation (2.1).

An alternative approach to estimating H-statistic uses a different dependent variable:

$$ln\,(R_{it}) = \alpha + \beta_{1i}\,ln(W_{1,it}) + \beta_{2i}\,ln(W_{2,it}) + \beta_{3i}ln(W_{3,it}) + \gamma_{1i}\,ln(Y_{1,it}) + \gamma_{2i}\,ln(Y_{2,it}) + \gamma_{3i}\,ln(Y_{3,it}) + \delta D + \varepsilon_{it} \quad , \tag{2.2}$$

where R_{it} is the ratio of total revenue to total assets (as a proxy for output price), W_1 is the ratio of interest expenses to total deposits and money market funding (as a proxy for the input price of deposits), W_2 is the ratio of personnel expense to total assets (as a proxy for the price of labour), and W_3 is the ratio of other operating and administrative expenses to total assets (as a proxy for the price of fixed capital), with i denoting bank i and t denoting time t. Y_1 is a control variable for the ratio of equity to total assets, Y_2 controls for the ratio of net loans to total assets, and Y_3 is the log of total assets. D is a vector of year dummies for 1998–2005. Equation (2.2) is also estimated using OLS with time dummies and GLS with fixed effects and time dummies.

The overall H-statistic is the average of the four estimation models[4]. The sum of the elasticities of revenue with respect to input prices is negative for monopolist, equal to 1 for a competitive price-taking firm and within the range of 0 to 1 for monopolistic competition. Some studies criticize the use of H-statistic as a measure of competition.

Bikker, Shaffer, and Spierdijk (2012) argue that the price equation is inappropriate for measuring competitive conduct, and that the relationship between the H-statistic and the competition is subjective to the selected cost function. Shaffer and Spierdijk (2015) demonstrate that higher values of the H-statistic may not reflect more competitive market conditions, and

[4] Schaeck et al. (2009) employed four different estimation methods and averaged the values of H-statistic to produce an estimate of the true value of H-statistic (page 715 – footnote 9).

there can be situations where the H-statistic is positive for a monopoly. As a result, this chapter considers other measures of competition in the later sections.

2.4.2 Duration analysis

Duration models with time-varying covariates model the time to transition from a stable banking system to a systemic banking crisis. When there is no crisis event for a particular country, then the full time span is considered for the analysis (i.e., a right-censored spell). Duration models are also able to take into account multiple crisis events per country. A positive sign indicates a longer time period until a country experiences a crisis event, hence greater stability. Diallo (2015); Schaeck et al. (2009) estimate the relationship between competition and stability using the duration model.

2.4.3 Logit analysis

Logit estimation is widely used in the literature to estimate the probability of experiencing a banking crisis (Beck, Demirgüç-Kunt, & Levine, 2006; Demirgüç-Kunt & Detragiache, 1998, 2005). SCW also employ the logit model where the estimation is run for a pooled sample.

$$LnL = \sum_{t=1 \ldots T} \sum_{i=1 \ldots n} \{P(i,t) ln[F(\beta' X(i,t))] + \left(1 - P(i,t)\right) \ln\left[1 - F\left(\beta' X(i,t)\right)\right] \} \quad , \tag{2.3}$$

where $P(i,t)$ is a dummy variable that takes the value "1" when a banking crisis occurs in country i at time t or "0" otherwise, β is the vector of coefficients, and $X(i,t)$ is a matrix of explanatory variables. $F(\beta' X(i, t))$ is the cumulative probability distribution function for the logistic distribution evaluated at $\beta' X(i,t)$ (Schaeck et al., 2009).

In the logit model, the coefficients estimate the effect of a change in the explanatory variables on the probability that a banking crisis occurs. The effect of a change in one variable depends on the values of all the explanatory variables. While the sign of the coefficient indicates the direction of the change, the size depends on the slope of the cumulative distribution function, which in turn depends on the value of $B'X(i,t)$. A variable that positively contributes to stability will have a negative coefficient in the logit estimation, indicating a lower probability of experiencing a crisis.

2.5 Replication of SCW

SCW generously provided their data and Stata do files to re-produce their results. The dependent variable in SCW's study is a dummy variable that takes the value 1 if a particular country in a particular year met one of the following four criteria: (i) emergency measures such as deposit freezes or bank holidays are implemented, (ii) large-scale bank nationalizations take place, (iii) nonperforming assets reach at least 10% of total assets, or (iv) fiscal cost of the rescue operations reach 2% of gross domestic production (GDP) (Schaeck et al., 2009). SCW obtain their data on bank crises from Demirgüç-Kunt and Detragiache (2005). The main explanatory variables are the H-statistic and the three-bank concentration ratio.

2.5.1 Summary statistics

Table 2.1 reports summary statistics published by SCW and the recalculated summary statistics using data provided by SCW. The reproduction exercise produces the same summary statistics, except GDP growth (lagged by one period) and the rate of inflation. Details of all the variables are given in Appendix 1[5]. The regression results of Tables 2.2 and 2.3 show that the data provided by SCW enable close matching of their regression results. As the data provided by SCW enabled close reproduction of their results, and as the summary statistics for GDP growth and the rate of inflation were substantially different from what they reported in their paper, this suggests that the summary statistics for these two variables were incorrectly reported in SCW.

[5] Data and Codes to reproduce the results of Tables 2.1 through 2.17 are available on https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/3HVWCB or https://github.com/SamangiBandaranayake/Are-Competitive-Banks-Stable-/tree/master/Chapter-do

Table 2.1

Summary Statistics

	Original			Replication		
	N	**Mean**	**Std. dev**	**N**	**Mean**	**Std. dev**
GDP growth (lag)	734	3.4505	3.3066	734	-0.0131	3.7523
Inflation	734	15.0287	43.5508	734	1.8835	1.1701
Real interest rate	734	1.1214	18.5509	734	1.1214	18.5509
Depreciation	734	2.188	3.0281	734	2.188	3.0281
Terms of trade	734	4.0984	2.0101	734	4.0984	2.0101
Credit growth	734	11.2683	28.7674	734	11.2683	28.7674
Moral hazard index	734	1.3058	0.7231	734	1.3058	0.7231
German legal origin	734	0.0886	0.2843	734	0.0886	0.2843
French legal origin	734	0.3965	0.4895	734	0.3965	0.4895
Scandinavian legal origin	734	0.0831	0.2762	734	0.0831	0.2762
British legal origin	734	0.3910	0.4884	734	0.3910	0.4883
Africa dummy	734	0.1267	0.3329	734	0.1267	0.3329
Other dummy	734	0.4482	0.4977	734	0.4482	0.4977
Latin America dummy	734	0.2057	0.4045	734	0.2057	0.4045
G10 dummy	734	0.2193	0.4141	734	0.2193	0.4141
Concentration	734	0.6734	0.1617	734	0.6734	0.1617
H-statistic (H1)	707	0.3224	0.207	707	0.3224	0.207
H-statistic (H2)	707	0.2915	0.2228		N/A	
Private credit/GDP	684	0.4485	0.3081	684	0.4485	0.3081
Foreign ownership	444	0.1499	0.1708	444	0.1499	0.1708
Government ownership	723	0.4697	0.3304	723	0.4697	0.3304
Activity restrictions	663	9.7345	2.2939	663	9.7345	2.2939

	Original			Replication		
	N	**Mean**	**Std. dev**	**N**	**Mean**	**Std. dev**
Entry restrictions	663	7.0573	1.5958	663	7.0573	1.5958
Capital regulatory index	663	6.2054	1.5667	663	6.2054	1.5667
Official supervisory power	663	10.6991	2.4318	663	10.6991	2.4318
Private monitoring index	511	8.1037	1.2379	511	8.1037	1.2379

Note. The left side of the table reports the original results of Columns (1), (2), and (3) of Table 1 in SCW (page 718) and the right side of the table reports the replication results from authors' data. N/A = the data to reproduce the alternative H-statistic is not available in the authors' dataset.

2.5.2 Replicating results in paper with provided data

The main results of the SCW's paper are presented in Table 3 (pages 722-723). SCW's Table 3 shows the results obtained with the duration model in columns (1) – (4) and logit model in columns (5) – (8). Columns (1) and (4) report coefficients of other control variables apart from H-statistic and concentration. Columns (2) and (6) include the H-statistic into the model. Bank concentration ratio is added to the model in columns (3) and (7). Finally, an interaction term between H-statistic and Concentration is added to columns (4) and (8).

Table 2.2 presents a comparison of the original paper and the replication of the duration models. The estimated coefficient results of the replication closely match SCW's results. The H-statistic in columns (2) is a positive coefficient of 1.6977 and is significant at the 10 percent significance level. The H-statistic in column (3) is also a positive coefficient of 2.3482 and is significant at the 5 percent significance level. It shows that the inclusion of the concentration variable increases the coefficient value of the H-statistic. A statistically significant positive coefficient value of H-statistic indicates that the time to crisis increases with greater competition and it supports the view that competition increases banking system stability.

The concentration variable in column (3) shows a positive coefficient of 3.0834 and is significant at the 1 percent significance level. It indicates that survival time is greater in a more concentrated banking system. Both H-statistic and concentration are statistically significant. This led SCW to conclude that these two variables are not the same and describe different characteristics of banking systems, with the H-statistic capturing the effect of competition, and concentration capturing the market share of large banks in the banking system.

In addition to the main explanatory variables, other control variables also describe the time to crisis. When there is a decrease in real interest rate, terms of trade, and credit growth, it is associated with an increase in time to crisis. Depreciation of the exchange rates increases the expected time to crisis. The moral hazard index shows that deposit insurance schemes decrease the time to crisis. Countries with French legal origin indicate that they are more likely to experience a crisis compared to countries with British legal origin. African countries tend to experience more crises compared to the G10 countries. Countries from other parts of the world, other than African and Latin American regions, are also likely to experience more crises compared to the G10 countries.

Table 2.2

Replication of Key Duration Models with Authors' Data

Variable	Column (2)		Column (3)	
	Original	Replication	Original	Replication
GDP growth (lag)	-0.0594	-0.0594	-0.0592	-0.0592
	(0.0365)	(0.0365)	(0.0377)	(0.0377)
Inflation	-0.1693	-0.1693	-0.1907	-0.1907
	(0.3200)	(0.3200)	(0.3457)	(0.3457)
Real interest rate	-0.0251**	-0.0251**	-0.0224*	-0.0224**
	(0.0121)	(0.0121)	(0.0114)	(0.0114)
Depreciation	0.0533*	0.0533*	0.0524*	0.0524*
	(0.0275)	(0.0275)	(0.0289)	(0.0289)
Terms of trade	-0.3126***	-0.3126***	-0.3043***	-0.3043***
	(0.0697)	(0.0697)	(0.0746)	(0.0746)
Credit growth	-0.0008**	-0.0008**	-0.0008***	-0.0008***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Moral hazard index	-0.4363**	-0.4363**	-0.4215*	-0.4215*
	(0.1785)	(0.1785)	(0.2279)	(0.2279)
German legal origin	-0.5967	-0.5967	-0.8851	-0.8851
	(1.0905)	(1.0905)	(1.0288)	(1.0288)
French legal origin	-1.0421**	-1.0421**	-1.3532***	-1.3532***
	(0.4511)	(0.4511)	(0.3887)	(0.3887)
Scandinavian legal origin	0.6542	0.6542	-0.0875	-0.0875
	(1.0942)	(1.0942)	(1.1386)	(1.1386)
Africa dummy	-1.5102**	-1.5102**	-1.8586***	-1.8586***
	(0.6586)	(0.6586)	(0.6682)	(0.6682)

Variable	Column (2)		Column (3)	
	Original	Replication	Original	Replication
Other dummy	-1.1901*	-1.1901*	-1.5535**	-1.5535**
	(0.6368)	(0.6368)	(0.6481)	(0.6481)
Latin America dummy	-0.5069	-0.5069	-0.4322	-0.4322
	(0.7557)	(0.7557)	(0.6853)	(0.6853)
H-statistic	1.6977*	1.6977*	2.3482**	2.3482**
	(0.8804)	(0.8804)	(0.9700)	(0.9700)
Concentration	----	----	3.0834***	3.0834***
			(0.9595)	(0.9595)
Observations	701	701	701	701

Note. This table reports the original results of SCW and the replication results of Columns (2) and (3) of Table 3 in SCW (page 722-723). The dependent variable is the log of time to crisis. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 2.3 compares logit estimates from the original paper with their respective replications[6]. H-statistic and Concentration are statistically significant at the 5 percent level. The negative coefficient values of H-statistic and Concentration indicate that the probability of a banking crisis is smaller for more competitive and more concentrated banking systems. Lagged values of GDP growth, inflation, terms of trade, and French legal origin are also statistically significant in the logit estimation model. GDP growth decreases the probability of crisis. Inflation and terms of trade indicate increase the probability of a crisis. Countries with French

[6] SCW report heteroscedasticity robust standard errors for their logit estimates. Table 2.3 follows the same procedure to report the results. However, in subsequent analysis this chapter uses cluster robust standard errors when estimating logit models. In most cases this reduced standard errors, enhancing statistical significance.

legal origin have a greater probability of experiencing crises compared to countries with British legal origin.

Both Tables 2.2 and 2.3 find that competition is positively associated with greater financial stability. Bank concentration is also positively associated with financial stability. Beck et al. (2006); Demsetz and Strahan (1997) also support the view that more concentrated banking systems can diversify their risk and be more stable. The replication results match the reported results of SCW and confirm SCW's findings using their data.

Table 2.3

Replication of Key Logit Models with Authors' Data

Variable	**Column (6)**		**Column (7)**	
	Original	**Replication**	**Original**	**Replication**
GDP growth (lag)	-0.2554***	-0.2554***	-0.2640***	-0.2640***
	(0.0773)	(0.0773)	(0.0842)	(0.0842)
Inflation	0.5328*	0.5328*	0.5125	0.5125
	(0.2985)	(0.2985)	(0.3154)	(0.3154)
Real interest rate	0.0306	0.0306	0.0290	0.0290
	(0.0193)	(0.0193)	(0.0222)	(0.0222)
Depreciation	0.0273	0.0273	0.0151	0.0151
	(0.0653)	(0.0653)	(0.0685)	(0.0685)
Terms of trade	0.2680***	0.2680***	0.2388***	0.2388***
	(0.0609)	(0.0609)	(0.0655)	(0.0655)
Credit growth	0.0006	0.0006	0.0006	0.0006
	(0.0006)	(0.0006)	(0.0006)	(0.0006)

Variable	Column (6)		Column (7)	
	Original	Replication	Original	Replication
Moral hazard index	0.5596	0.5596	0.4734	0.4734
	(0.3550)	(0.3550)	(0.3803)	(0.3803)
German legal origin	0.2724	0.2724	0.5139	0.5139
	(1.2038)	(1.2038)	(1.1809)	(1.1809)
French legal origin	0.8124	0.8124	1.2292**	1.2292**
	(0.6748)	(0.6748)	(0.6031)	(0.6031)
Scandinavian legal origin	0.1937	0.1937	1.1016	1.1016
	(0.9042)	(0.9042)	(0.8323)	(0.8323)
Africa dummy	0.6712	0.6712	1.0718	1.0718
	(0.9422)	(0.9422)	(0.9226)	(0.9226)
Other dummy	0.5525	0.5525	0.9495	0.9495
	(0.6716)	(0.6716)	(0.7398)	(0.7398)
Latin America dummy	-0.7543	-0.7543	-0.8618	-0.8618
	(0.8183)	(0.8183)	(0.8182)	(0.8182)
H-statistic	-2.3116**	-2.3116**	-2.9703**	-2.9703**
	(1.0644)	(1.0644)	(1.2328)	(1.2328)
Concentration	----	----	-3.4672**	-3.4672**
			(1.4747)	(1.4747)
Observations	707	707	707	707

Note. This table reports the original results and the replication results of Columns (6) and (7) of Table 3 in SCW (page 722-723). The dependent variable takes the value 1 if there has been a systemic crisis for that country in that year, and 0 otherwise. The numbers in parentheses below estimated coefficients are heteroscedasticity robust standard errors, as per SCW's analysis. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

2.6 Updating the Control Variables

The next step of the replication exercise is to update the values of control variables to examine if substituting updated values gives the same results. The Data Appendix in SCW provided the data sources they used for their data collection. For example, SCW use World Bank Development Indicators (WDI) to obtain values for GDP growth, inflation, and terms of trade. They use International Financial Statistics (IFS) for depreciation.

This chapter uses the same data sources as SCW to update their variables, as well as some alternative data sources. Van-Bergeijk (2016) reports that macroeconomic data are continuously being updated and different versions can differ substantially. This chapter also finds that there are substantial differences between the original data provided by SCW and the updated data. For example, Inflation for Brazil in 1980 is 4.5% in SCW's data. But, it is 87.3% from the currently reported value from the same data source WDI. To maintain the accuracy of data, another alternative data source is considered. Inflation for Brazil in 1980 is 91.2% in IFS. That value is different from both the original dataset and WDI, but still closer to the latter. In updating the data, several problems were encountered. First, SCW's original dataset contains values for variables for which corresponding values are not available in either the updated, same data source or alternative data sources. This leads to a reduction in the number of observations in the updated dataset. The second problem is that the same source no longer provides the historical data. In such instances, an alternative data source was used if possible.

Table 2.4 presents the differences in the original and updated data. It reports descriptive statistics for various data sources using a common set of observations to ensure that any differences presented in the Table 2.4 are mainly due to changes in the variable values. In this case, to be included in the table, the observation must fulfil two criteria; (i) the observation has been used in the estimation of column (3) of Table 3 in SCW (page 722-723), and (ii) the observation is available in the updated data. This assures that differences are not due to changes in observations from different countries or different time periods.

The top panel of Table 2.4 reports descriptive statistics for lagged GDP growth from three data sources: SCW's original dataset, WDI, and IFS. There are 699 common observations from all three data sources. An asterisk indicates that this is the data source used by SCW. The original dataset of SCW produces a mean lagged GDP growth rate of -0.0197%. For the same observations, WDI and IFS data provide a mean lagged GDP growth rates of 3.556% and 3.679%, respectively. This shows differences in the original and updated data. This is a common problem for all the control variables in Table 2.4. Data from alternative sources give similar values compared to the updated values from the same source used by SCW. This confirms that the original data reported by SCW and current data from the same data source are not compatible. Sections 2.5.1 and 2.5.2 investigate whether SCW's findings are maintained when the regressions are re-estimated with the updated control variables.

Table 2.4

Descriptive Statistics for Original and Updated Data (Common Observations)

Variable	**Data Source**	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
	Original	699	-0.0197	3.731	-17.333	25.572
GDP growth (lag)	WDI*	699	3.556	3.399	-13.128	21.829
	IFS	699	3.679	3.797	-8.857	52.554

Variable	Data Source	N	Mean	Std. Dev.	Min	Max
Inflation	*Original*	691	1.854	1.166	-4.257	6.439
	WDI*	691	15.085	45.013	-0.929	625.802
	IFS	691	15.169	44.896	-4.410	620.840
	DataMarket	691	15.085	45.013	-0.929	625.802
Depreciation	*Original*	332	2.835	2.546	-4.760	8.868
	IFS*	332	0.083	0.250	-0.282	3.219
	WDI	332	0.083	0.250	-0.282	3.219
	DataMarket	332	0.083	0.250	-0.282	3.219
Terms of trade	*Original*	404	4.626	0.197	3.931	5.305
	WDI*	404	0.312	10.945	-46.653	67.797
	DataMarket	404	1.409	15.754	-63.605	169.845
Real interest rate‡	*Original*	591	2.159	16.931	-312.233	41.110
	WDI	591	7.231	9.505	-35.078	76.428
	DataMarket	591	7.225	9.505	-35.078	76.428
Credit growth‡	*Original*	698	108.092	282.845	-811.882	3393.340
	WDI	698	15.887	93.366	-1605.175	541.081
	GFDD	698	15.759	93.416	-1605.175	541.081
Moral hazard index‡	*Original*	544	1.664	0.259	0.000	1.940
	DID	544	0.289	2.774	-11.862	4.618

Note. The values in the table make a comparison of descriptive statistics across different data sources. “Original” refers to the data provided by SCW. The other data sources are World Development Indicators (WDI), International Financial Statistics (IFS), Global Financial Development Database (GFDD), Deposit Insurance Database (DID), and DataMarket. Table 2.4 reports descriptive statistics for various data sources using a common set of observations. This ensured that differences were due to different values across data sources, and not because different observations were used to calculate the descriptive statistics. An asterisk indicates that the particular data source was used by SCW.

‡ indicates a different data source use to update the data. The reasons are given below.

Real interest rate: SCW state that they calculated real interest rates as "nominal interest rate minus the rate of inflation" and data sourced from International Financial Statistics (IFS). However, IFS reports various interest rates and inflation rates. The available interest rates are Central Bank policy rate, money market rate, Treasury bill rate, deposit rate, lending rate and government bond rates. The available inflation rates are consumer price index and GDP deflator. Not knowing the exact rates used by SCW to calculate their real interest data, researcher instead used the variables identified as "real interest rate" in WDI and DataMarket databases when updating the data.

Credit growth: Credit growth is based on the domestic credit to the private sector. SCW used IFS data in their paper. However, these data are not currently available from IFS. Therefore, WDI and GFDD databases are used when updating the data.

Moral hazard index: SCW obtained data for their moral hazard index from Demirgüç-Kunt and Detragiache (2002). These data were updated by Demirgüç-Kunt, Kane, and Laeven (2014). The updated values for this variable are collected from this latter source.

2.6.1 Re-estimating the key models for common observations

Table 2.5 reports a comparison of estimated results using original and updated data from the same data source for the same time period (1980-2005). This table uses updated control variables with SCW's H-statistic and concentration values. These results are based on common observations. SCW's paper reports results from 701 observations for the duration models and 707 observations for the logit models. However, when setting common observations, the number of observations drops to 222 for the duration models and 218 for the logit models. The H-statistic is statistically significant at the 5 percent level in three of the columns (2, 6, and 7) using the original data. However, when re-estimated with the updated data, the statistical significance of the H-statistic disappears. The coefficient values report the same sign as the original data, however the average of the associated t-statistics drops from 2 to 1. For example, the t-statistic of H-statistic is 2.17 in panel A - column (2). It drops to 1.23 in panel B - column (2). Note that any differences in estimates are exclusively due to updating the variables, and not due to differences in the composition of the samples, since the observations are the same. Turning to the concentration variable, it is not statistically significant at the 5 percent level using either the original or the updated data.

Table 2.5

Replication of Key Models Using Updated Data (Same Source) /Common Observations

Variable	**Duration models**		**Logit models**	
	(2)	**(3)**	**(6)**	**(7)**
Panel A: Original data				
H-statistic	2.7960**	1.9825	-5.9893***	-5.4947**
	(1.2908)	(1.7485)	(2.2759)	(2.2470)
Concentration	----	5.7003	----	-4.3380
		(3.9084)		(3.7786)
Observations	222	222	218	218
Panel B: Updated data – Same sources				
H-statistic	3.9171	3.3610	-4.6618	-4.1897
	(3.1742)	(3.3713)	(3.4343)	(3.8093)
Concentration	----	3.9562	----	-4.3421*
		(2.6326)		(2.3198)
Observations	222	222	218	218

Note. The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722 and 723). Only the competition and concentration coefficients are reported. All datasets used in the table consist of subsamples of the observations used to estimate the original specifications in SCW. The table consists of two panels. Panel A uses SCW's original dataset and panel B uses updates variable values from the same data sources as SCW. Both panels use the identical set of observations. Note that there are variables values that are available in SCW's original dataset, for which updated values are not available; and variables for which current values are available, but for which values are missing in SCW's original dataset. For this reason, the number of observations in each panel is less than the original number of observations used by SCW. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 2.6 repeats the same exercise as Table 2.5. Table 2.5 limits the data collection to the same data sources used by SCW. Table 2.6 collects data from alternative sources to increase the number of observations. The data source is decided based on the maximum number of observations. This table also uses a common set of observations for data collected from multiple sources. There are 474 observations for the duration models and 479 observations for the logit models. Panels A and B use the same set of observations.

Panel A, using the original data before updating, shows coefficient values of the H-statistic variable that are of the expected sign and statistically significant at the 5 percent level, confirming the view that competition increases stability. The updated data from multiple sources also produce estimated coefficients of the same sign and similar size compared to the original data. However, in none of the columns is H-statistic statistically significant at the 5 percent level. The concentration variable is statistically significant in both panels. The coefficient values of H-statistic indicate that statistical significance depends on the data vintage.

Table 2.6

Replication of Key Models Using Updated Data (Multiple Sources) /Common Observations

Variable	Duration models		Logit models	
	(2)	**(3)**	**(6)**	**(7)**
Panel A: Original data				
H-statistic	2.5688**	2.6843**	-3.8997***	-4.6277***
	(1.1370)	(1.2699)	(1.3488)	(1.4535)
Concentration	----	4.8737*	----	-5.3242**
		(2.6118)		(2.2109)
Observations	474	474	479	479
Panel B: Updated data – Multiple Sources				
H-statistic	2.9316*	3.5204	-3.1329*	-3.7062*
	(1.5956)	(2.2027)	(1.6277)	(2.1125)
Concentration	----	4.4773***	----	-4.9514***
		(1.5671)		(1.4539)
Observations	474	474	479	479

Note. The column headings of the table indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722 and 723). Only the competition and concentration coefficients are reported. Panel A uses SCW's original dataset. Panel B expands the number of data sources, choosing the one that maximizes the number of observations available for estimation. Both panels use identical sets of observations. Note that there are variable values that are available in SCW's original dataset, for which updated values are not available; and variables for which current values are available, but where values were missing in SCW's original dataset. For this reason, the number of observations in each panel is less than the original number of observations used by SCW. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

2.6.2 Re-estimating the key models for maximum observations

Tables 2.5 and 2.6 present results for common observations in order to focus on the effect of data updating with identical observations. This section re-estimates the models using all available observations. Table 2.7 presents results in two panels. Panel A reports estimation results from the same data source used by SCW. Panel B reports results from multiple data sources.

Strikingly, H-statistic is now statistically insignificant in both panels A and B. Further, the estimated coefficient values are relatively small compared to previous results in Table 2.2 and 2.3. However, the results show the same relationship between competition and stability. For example, in Column (2) of Table 2.2, SCW's reported coefficient value of H-statistic is 1.6977. The associated coefficient estimates are 0.9160 and 0.2551 in panels A and B, respectively. The associated t-statistic is 1.93 in Table 2.2, compared to t-statistics less than 1 in both panels of Table 2.7. In contrast, the results for the concentration variable continue to confirm SCW's findings, achieving statistical significance at the 5 percent level or better.

Table 2.7

Replication of Key Models Using Updated Data: 1980-2005

Variable	**Duration models**		**Logit models**	
	(2)	**(3)**	**(6)**	**(7)**
Panel A : Same sources (1980-2005)				
H-statistic	0.9160	0.3447	-0.5822	-0.0653
	(1.2239)	(1.3776)	(0.7937)	(0.9521)
Concentration	-	4.4016**	-	-4.3776**
		(1.8738)		(1.7657)
Observations	327	327	331	331
Panel B: Multiple sources (1980-2005)				
H-statistic	0.2551	0.3110	-0.0580	-0.1678
	(0.9266)	(0.9797)	(0.9519)	(1.0370)
Concentration	-	4.6350***	-	-4.9581***
		(1.4047)		(1.5135)
Observations	679	679	682	682

Note. The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722-723). Only the competition and concentration coefficients are reported. Panels A and B are identical to panel B in Tables 2.5 and 2.6, except that all available observations are used, even if the observations were not included in SCW's original analysis. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Overall, the results for H-statistic using the updated data have the same sign as the original estimates. However, the estimated coefficients are smaller in absolute value and statistically insignificant. Therefore, the updated data fail to confirm that more competition leads to greater financial stability. The concentration variable is consistent with the findings reported by SCW, with coefficient sizes of approximately the same size, and statistically significant.

2.7 Estimation of Results with an Extended Sample Period

The previous sections of this chapter used data from the same sample period of 1980-2005 as SCW. Since updated data from the same data sources and multiple sources failed to confirm the findings of SCW with respect to competition, the next step is to extend the sample period to year 2011. This step focuses on three areas: Firstly, it uses updated control variables from multiple sources for the period 1980-2011. Secondly, it updates H-statistic and the concentration variable from the GFDD database. The GFDD database provides country-level concentration values from 1996 and H-statistic values from 2010. Therefore, the estimations use SCW's concentration values for 1980-1995 and SCW's H-statistic values for 1980-2009. Thirdly, it updates the dependent variable from the Laeven and Valencia (2012) Systemic Banking Crises Database.

The estimation results are presented in Table 2.8. The results are presented in three panels. All three panels use updated control variables from multiple sources. Table 2.8 considers various combinations of ways to incorporate the updated H-statistic and concentration values. Panel A uses the same values of H-statistic and Concentration as SCW throughout the entire sample period 1980-2011. Panel B uses two sets of constant values for both H-statistic and Concentration. For the first time period from 1980-2009, it uses SCW's (constant) H-statistic values. For the second time period, it uses an average, country level H-statistic value calculated from the updated data for the time period 2010-2011. With respect to Concentration, it uses SCW's (constant) concentration values from 1980-1995 for the first period. For the second period, it uses country-level averages from 1996-2011. Panel C uses SCW's constant H-statistic for 1980-2009, and time-varying, H-statistic values for 2010-2011. For Concentration, it uses a constant concentration for 1980-1995, and time-varying values for 1996-2011.

The estimated coefficients of H-statistic are small and statistically insignificant in all three panels. The concentration variable has the same sign in all three panels, and implies that Concentration positively contributes to financial stability. However, the size and statistical significance of the coefficients are different. Panel A reports statistically significant Concentration coefficients at the 1 percent level. In Panel B, it shows a weak statistical significance. It is small and insignificant in panel C.

The estimated coefficients for H-statistic are relatively small compared with SCW's reported values, and the associated t-statistics are less than 1. The results for the concentration variable are mixed, with no way of identifying which set of results from panel A, B, or C is best. Overall, these findings cannot be said to support SCW's conclusions.

Table 2.8

Replication of Key Models Using Updated Data: 1980-2011

Variable	**Duration models**		**Logit models**	
	(2)	**(3)**	**(6)**	**(7)**
Panel A: Constant H-Statistic and Concentration values: whole period				
H-statistic	0.1285	0.1201	0.0251	-0.0028
	(0.8489)	(0.9120)	(0.8696)	(0.9769)
Concentration	-	4.4092***	-	-4.6377***
		(1.2183)		(1.3097)
Observations	803	803	802	802
Panel B. Constant H-statistic and Concentration values: two periods				
H-statistic	0.2899	0.3480	-0.2841	-0.4065
	(0.8437)	(0.7830)	(0.8067)	(0.7630)
Concentration	-	2.6524*	-	-2.7918*
		(1.3919)		(1.4608)
Observations	803	803	802	802
Panel C. Mixed constant, time-varying H-statistic and Concentration values				
H-statistic	0.2827	0.3157	-0.2836	-0.3192
	(0.8375)	(0.7948)	(0.8048)	(0.7722)
Concentration	-	1.3664	-	-0.8524
		(1.1118)		(1.1031)
Observations	803	803	802	802

Note. The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722-723). Only the competition and concentration coefficients are reported. All three panels of estimates use multiple sources to achieve maximum number of observations with updated data. The values of the control variables across the three panels are identical and used updated values from multiple sources. The values for H-statistic and Concentration differ as follows: Panel A uses SCW's (constant) values for the entire time period (1980-2011). Panels B and C accommodate the availability of updated H-statistic and Concentration data for the years 2010-2011 and 1996-2011, respectively. Panel B uses two sets of constant values for each variable. For H-Statistic, it uses SCW's value for 1980-2009 and the country average of H-statistic for 2010-2011. For Concentration, it uses SCW's value for 1980-1995, and the country average of Concentration for 1996-2011. Panel C uses SCW's H-Statistic for 1980-2009 and the time-varying H-statistic for 2010-2011. For Concentration, SCW's Concentration for 1980-1995 and the time varying Concentration for 1996-2011. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

2.8 Z-score as a Measure of Financial Stability

The dependent variable of SCW's paper is a dummy variable that takes the value of one if a systemic crisis is observed in a particular year, and zero otherwise. SCW get the data from the systemic crisis database produced by Demirgüç-Kunt and Detragiache (2005). Since there is no unique measure to capture financial stability, the next step of the analysis is to use an alternative measure of financial stability. Z-score is one of the common measures used in the literature to measure the financial stability.

Z-score is a bank-level risk measure that estimates the inverse probability of default at the individual level of banks. Increases in Z-score indicate a lower probability of default, and thus more financial stability. The measure compares a bank's capital buffer and returns, with return volatility (Boyd, Graham, & Hewitt, 1993; Boyd & Runkle, 1993).

As a measure of country-level stability, a number of studies use an aggregated bank-level Z-score (The World Bank, 2016; Uhde & Heimeshoff, 2009; Yeyati & Micco, 2007). This section follows that approach and uses country-level Z-scores to estimate the relationship between competition and stability. Z-score is estimated as follows:

$$Z - score_{it} = \frac{ROA_{it} + \left(\frac{Equity_{it}}{Assets_{it}}\right)}{Stdev\ (ROA)_{it}}; \tag{2.4}$$

where *ROA* is country-level return on assets; *Equity,* and *Assets* are country-level aggregates; *stdev(ROA)* is the standard deviation of *ROA; i* denotes country *i* and *t* denotes time *t.*

GFDD provides country-level Z-scores using aggregated bank-level data. Data are available for 1999-2015. Therefore, the subsequent empirical analysis focuses on the period 1999-2015. Because of the probability nature of the Z-score data, fractional response regression is employed to estimate the results.

Table 2.9 presents the results using Z-score as the stability measure. There are two panels in the table. Panel A uses two sets of H-statistic and concentration values. SCW's constant H-statistic values are used for the first period of 1999-2009. For the second time period of 2010-2015, an average country-level H-statistic is calculated. The concentration variable uses two, country-level average values for 1999-2007 and 2008-2015. Panel B uses a constant H-statistic for 1999-2009, and time-varying H-statistic values for 2010-2015; and time-varying concentration values for the entire 1996-2015 period.

Column (1) of both panels A and B estimate a specification with just H-statistic and column (2) includes both H-statistic and Concentration. A positive coefficient estimate of H-statistic and Concentration indicates that the variable is positively associated with financial stability. In panel A, the estimated coefficients for H-statistic are negative, while being positive in panel B. The concentration variable indicates a positive relationship in both panels. However, the estimated coefficients are statistically insignificant. The results of Table 2.9 demonstrate that when using an alternative measure of stability, SCW's conclusions are not supported.

Table 2.9

Replication Using Z-Score as the Stability Measure: 1999-2015

Variable	**Panel A: Constant H-statistic and Concentration values: two periods**	
	(1)	**(2)**
H-statistic	-0.0253 (0.3974)	-0.0544 (0.3919)
Concentration	-	0.5832 (0.3904)
Observations	384	384
	Panel B: Mixed constant, time-varying H-statistic and Concentration values	
H-statistic	0.0192 (0.3492)	0.0039 (0.3549)
Concentration	-	0.4770 (0.3098)
Observations	384	382

Note. This table uses Z-score as the dependent variable. All other control variables remain the same. Only the competition and concentration coefficients are reported. Constant and time-varying values of H-statistic and Concentration are used for estimations. The values of H-statistic and Concentration differ as follows: Panel A uses two sets of constant variables for H-statistic and Concentration. For H-statistic, it uses the SCW's (constant) H-statistic value for the period 1999-2009, and the country average of H-statistic for 2010-2015. For Concentration, it uses the country averages for 1999-2007 and 2008-2015, respectively. Panel B maximizes the use of time-varying values. For H-statistic, it uses the SCW's (constant) H-statistic value for the period 1999-2009, and the time-varying values of H-statistic for 2010-2015. For Concentration, it uses time-varying values over the entire, 1999-2015 period. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country.

2.9 Estimation of the Effect Size

The discussion up to this point has mainly focused on the statistical significance of H-statistic and Concentration. This section examines the estimated economic significance of these variables. Table 2.10 uses estimates from the logit model in Table 2.8, panel B, column (7); and the fractional logistic regression model of Table 2.9, panel A, column (2). In Table 2.8, the probability denotes the probability of a systemic crisis. In Table 2.9, the probability denotes the inverse probability of default of a country's banking system. To measure economic significance, the table considers an increase in the respective variables from their 25th percentile to their 75th percentile value.

In panel A, an increase in H-statistic from its 25th percentile to 75th percentile value is associated with a reduction in the probability of a crisis of 0.0010. The direction of the effect is consistent with the view that more competition is associated with greater stability. In panel B, the same size change in H-statistic is associated with a reduction in the inverse probability of default by 0.0017, also consistent with the view that more competition is associated with financial instability. The small sizes of these effects indicate an economic insignificance that is consistent with their statistical insignificance in Tables 2.8 and 2.9.

In contrast, the estimated effects for Concentration are much larger compared to H-statistic. In panel A, an increase in the concentration variable from its 25th percentile to 75th percentile value is associated with a reduction in the probability of a crisis of 0.0196. This is economically as well as statistically significant given the generally low probability of a crisis occurring in a given year. In contrast, the same size change in panel B reports an increase in the inverse probability of default of 0.0171, which is opposite in sign to the effect in panel A. However, the estimates on which these effects are calculated are statistically insignificant in Table 2.9, so that the opposite effects may be accounted for by the imprecision of the underlying estimates.

Table 2.10

Effect Size Estimates- Evaluating Predicted Probabilities at the 25th, 50th, and 75th Percentile Values of H-statistic and Concentration

	Obs.	***H-statistic***	***Concentration***
Panel A: Probability of a crisis (from Table 2.8, Panel B, Column 7)			
25th Percentile	803	0.0257	0.0371
50th Percentile	803	0.0254	0.0283
75th Percentile	803	0.0247	0.0175
Δ (75th-25th)	---	*-0.0010*	*-0.0196*
Panel B: Inverse probability of a default (from Table 2.9, Panel A, Column 2)			
25th Percentile	384	0.1107	0.1020
50th Percentile	384	0.1102	0.1058
75th Percentile	384	0.1090	0.1191
Δ (75th-25th)	---	*-0.0017*	*+0.0171*

Note. The predicted probabilities for panel A are derived from the estimated logit model of Table 2.8, Panel B, Column (7). The dependent variable in that equation is the dummy variable indicating an occurrence of a systemic crisis. The predicted probabilities for panel B are derived from the estimated fractional logit model of Table 2.9, Panel A, Column (2). The dependent variable in that equation is the country's Z-score. All probabilities are calculated at the mean values of the regression covariates, except for the variable of interest (H-statistic or Concentration) which are evaluated at their 25th, 50th, and 75th percentile values (ascending order).

2.10 Alternative Competition Measures

In the literature, H-statistic, Lerner index, and Boone indicator are all common measures of competition. This section uses Lerner index and Boone indicator as alternative measures of competition[7].

2.10.1 Lerner index

The Lerner index is a bank-level competition measure that measures market power of the bank. The "price" of the bank is calculated as the bank's total revenue over assets. Marginal costs are obtained from an estimated trans-log cost function with respect to the output of the bank. Increases in the Lerner index indicate less competition. The degree of competition is a decreasing function of the index, which takes values between 0 and 1. In the case of perfect competition, the Lerner index equals 0. Under pure monopoly, the Lerner index equals 1 (Beck, De Jonghe, & Schepens, 2013; Berger, Klapper, & Turk-Ariss, 2009; Diallo, 2015; Fernández de Guevara, Maudos, & Pérez, 2007; Fu, Lin, & Molyneux, 2014; Leon, 2015; Maudos & Solís, 2011).

The Lerner index is not a perfect measure of competition. Spierdijk and Zaouras (2016) find the interpretation of the Lerner index is valid only when firms maximize their revenue subject to a minimum profit constraint. Aggregated country-level Lerner index data are available from GFDD from 1996-2015. The bank-level Lerner index is computed as:

[7]This chapter briefly explains the non-structural measures. For a detail discussion of non-structural measures, see Chapter Five.

$$Lerner_{it} = \frac{P_{it} - MC_{it}}{P_{it}}, \tag{2.5}$$

where P is the ratio of total revenue to total assets, and MC is the marginal cost of bank i in year t.

2.10.2 Boone indicator

The Boone indicator is based on relative profit differences (Boone, 2008). It is calculated as the elasticity of profits to marginal costs (Boone, 2008; Duygun, Shaban, & Weyman-Jones, 2015). More efficient banks, or banks with low marginal costs, are able to maintain high profits compared to their less efficient rival firms. Higher (less negative) values of Boone indicate less competitiveness in the banking industry (Diallo, 2015; S. Kasman & A. Kasman, 2015; Leon, 2015; Schaeck & Cihak, 2008, 2014). Both H-statistic and the Lerner index are price-based measures, while the Boone-indicator is a profit-based measure. The problem with the Boone indicator is that the efficiency may not be immediately reflected in short term profits, and the Boone indicator ignores this (Leon, 2015). The calculation of bank-level Boone indicator is as follows:

$$\pi_{it} = \alpha + \beta \ln(C_{it}), \tag{2.6}$$

where π_{it} measures profit of bank i at time t, β is the Boone indicator, and C_{it} is marginal cost.

Schaeck and Cihak (2010) use average cost as a proxy for marginal cost since marginal cost is not directly observable. GFDD provides the values of the Boone indicator for each country by following Schaeck and Cihak (2010) approach. Aggregated Boone indicator values for each country are available from 1999 to 2015.

2.10.3 Correlations between H-statistic, Lerner index, Boone indicator, and Concentration

The literature has used H-statistic, the Lerner index, the Boone indicator, and Concentration as alternative measures of competition. Panzar and Rosse (1987) H-statistic measures the transmission of input costs to revenue. The Lerner index captures market power based on price. The Boone indicator measures competition based on efficiency. And Concentration is the market share of the largest banks in the market. Therefore, it is worthwhile to examine the correlation between these measures.

Table 2.11

Pairwise Correlations for the Three Competition Variables and Concentration

	H-statistic	**Lerner**	**Boone**	**Concentration**
H-statistic	Obs = 270	---	---	---
Lerner	-0.1070 p-value = 0.095 Obs = 245	Obs = 737	---	---
Boone	-0.0436 p-value = 0.476 Obs = 270	-0.0073 p-value = 0.843 Obs = 735	Obs = 761	---
Concentration	0.1807 p-value = 0.003 Obs = 270	0.0113 p-value = 0.760 Obs = 732 ——— 0.0286 p-value = 0.656 Obs = 245	0.0968 p-value = 0.008 Obs = 756 ——— 0.0092 p-value = 0.881 Obs = 270	Obs = 757

Note. Number of pairwise observations differ because the availability of updated, time-varying observations. The updated data availability is as follows: H-statistic: 2010-2015; Lerner: 1996-2015; Boone: 1999-2015; Concentration: 1996-2015.

Table 2.11 provides pairwise correlations for all four measures. The availability of data is different for the four measures. H-statistic is available for 2010-2015, the Lerner index for 1996-

2015, the Boone indicator for 1999-2015, and Concentration for 1996-2015. This leads to a variation in the number of observations for the respective pairwise correlations.

Increases in the Lerner index and the Boone indicator are associated with a decrease in competition. In contrast, an increase in the H-statistic is associated with greater competition. Therefore, a negative correlation should exist between H-statistic / Boone and H-statistic/ Lerner. Table 2.11 confirms the expected signs of the correlations. However, the correlation values are small in size and not statistically significant at the 5 percent level. These results are consistent with the findings of Leon (2015) and suggest that these measures may be capturing different aspects of competition.

The pairwise correlations with Concentration, H-statistic and the Boone indicator show a statistically significant, positive correlation. The Lerner index also shows a positive correlation, though it is statistically insignificant. These correlations seemingly contradict the negative relationship between H-statistic / Boone and H-statistic / Lerner. To be consistent, Boone and Lerner should show an inverse relationship with Concentration. However, correlation is not always transitive (Giles, 2015). As a result, the pairwise correlation between Concentration and H-statistic does not necessarily determine the sign of the correlation between Concentration and the Lerner index or Concentration and the Boone indicator.

One possible reason for this is that the respective correlations are based on different sets of observations. To address this problem, the Lerner index, the Boone indicator, and Concentration were restricted to cover the same time period as H-statistic (2010-2015). When this is done, while the signs of the correlations remain the same, the correlations for Lerner /

Concentration and Boone / Concentration both become statistically insignificant, with the Boone / Concentration correlation decreasing in size by an order of magnitude. This highlights the time-varying nature of the relationships between the respective measures of competition.

2.10.4 Estimation of the results with alternative measures

To estimate the relationship between competition and stability, the Lerner index and the Boone indicator values are substituted for H-statistic in the Column (2), (3), (6) and (7) specifications of Tables 2.1 and 2.2. Everything else is held constant. Panel A reproduces the estimates of the coefficients for H-statistic and Concentration from Tables 2.2 and 2.3[8]. Panels B and C use constant values for the Lerner and Boone variables for the entire time period (1980-2005), where Lerner and Boone are equivalent to their average value over the periods 1996-2005 and 1999-2005, respectively.

Table 2.12 summarizes the estimated results from the duration and logit models. Panels B and C replaces the H-statistic with Lerner index and Boone indicator. If the alternative measures for competition are consistent with the H-statistic, the respective coefficients would need to have an opposite sign. The coefficient of Lerner reports the correct sign only in column (2). The coefficients of Boone report the correct sign in columns (6) and (7). However, the results are statistically insignificant in both panels. These results indicate that SCW's conclusions rely entirely on using H-statistic as a measure of competition. If they had used a different measure of competition, they would not have come to the same conclusion.

[8] Table 2.3 reports heteroscedasticity robust standard errors by following SCW's procedure. However, Table 2.12 uses cluster robust standard errors when estimating logit models. In most cases this reduced standard errors and it enhances the statistical significance.

Table 2.12

Replication of Key Models Using Alternative Competition Variables: 1980-2005

Variable	**Duration models**		**Logit models**	
	(2)	**(3)**	**(6)**	**(7)**
Panel A: Original data				
H-statistic	1.6977*	2.3482**	-2.3116**	-2.9703**
	(0.8804)	(0.9700)	(0.9632)	(0.9776)
Concentration	----	3.0834***	----	-3.4672**
		(0.9595)		(1.0810)
Observations	701	701	707	707
Panel B: Replacing H-Statistic with Lerner				
Lerner	-0.1127	1.3756	-0.5129	-2.0041
	(3.9383)	(3.2663)	(4.1361)	(3.6113)
Concentration	----	2.8603***	----	-3.1270***
		(1.1774)		(1.1842)
Observations	701	701	707	707
Panel C: Replacing H-Statistic with Boone				
Boone	0.0953	-0.3284	1.5462	2.4372
	(1.9716)	(1.9685)	(2.3286)	(2.7049)
Concentration	----	2.7326**	----	-3.1452**
		(1.1155)		(1.3252)
Observations	701	701	707	707

Note. The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722-723). Only the competition and concentration coefficients are reported. Panel A reproduces the estimates from Tables 2.2 and 2.3. Panels B and C use the identical set of observations, so that the only difference across panels for a given specification is that a different competition variable has been used (Lerner or Boone instead of H-statistic). Panels B and C use constant values for these variables for the entire time period (1980-2005), whereas Lerner and Boone are set equal to their average value over the periods for which data are available: i.e. 1996-2005 and 1999-2005, respectively. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 2.13

Replication of Key Models Using Alternative Competition Variables: 1980-2011

Variable	**Duration models**		**Logit models**	
	(2)	**(3)**	**(6)**	**(7)**
Panel A: Lerner and Concentration				
Lerner	-3.3127	-3.3339	3.4268	3.7713
	(2.4912)	(2.5982)	(2.6801)	(2.7738)
Concentration	-	4.3418***	-	-4.5865***
		(1.1696)		(1.2695)
Observations	803	803	802	802
Panel B: Boone and Concentration				
Boone	-0.4944	-1.0170**	0.5663	1.1100*
	(0.3979)	(0.4180)	(0.4509)	(0.5698)
Concentration	-	4.8557***	-	-5.0795***
		(1.2454)		(1.3526)
Observations	803	803	802	802

Note. The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722-723). Only the competition and concentration coefficients are reported. Panels A and B use constant values for these variables for the entire time period (1980-2011), whereas Lerner and Boone are set equal to their average value over the periods for which data are available: i.e.1996-2011 and 1999-2011, respectively. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 2.13 estimates the relationship between competition and stability by using alternative competition measures, extending the sample period to 2011, and updating all the other control variables. Panel A reports the estimation results using the Lerner index, and panel B reports results using the Boone indicator. The coefficients confirm that increased competition has a positive association with the financial stability. However, the results are statistically significant at the 5 percent level in only one case: panel B, column (3).

Table 2.14

Replication of Key Models Using Updated Data and All the Competition Variables: 1980-2011

Variable	Duration models (2)	Duration models (3)	Logit models (6)	Logit models (7)
Panel A: Constant values: whole period				
H-statistic	-0.4568	-0.6599	0.6520	0.9250
	(0.9483)	(1.1343)	(0.9236)	(1.1771)
Lerner	-3.6815	-3.8679	4.0123	4.7302
	(2.7352)	(3.2869)	(2.8382)	(3.5410)
Boone	-0.5113	-1.0771**	0.6351	1.2416*
	(0.4157)	(0.5173)	(0.5073)	(0.7544)
Concentration	-	4.8944***	-	5.2185***
		(1.3272)		(1.4834)
Observations	803	803	802	802
Panel B: Constant values: two periods				
H-statistic	1.1101	1.0641	-0.3897	-0.5457
	(1.0461)	(0.9770)	(0.9105)	(0.8427)
Lerner	5.6094*	6.1103**	-0.5487	-1.1863
	(2.9749)	(2.7840)	(3.6257)	(3.4246)
Boone	0.6088	0.3009	-0.4325	-0.1566
	(1.0289)	(1.0397)	(1.1504)	(1.1735)
Concentration	-	3.1853*	-	-2.8637*
		(1.6804)		(1.4716)
Observations	803	803	802	802

Variable	Duration models		Logit models	
	(2)	(3)	(6)	(7)
Panel C: Mixed constant and time-varying values				
H-statistic	0.5999	0.6229	-1.1331	-1.1656
	(0.9218)	(0.8774)	(1.0930)	(1.0683)
Lerner	2.1977	2.5437	-5.2821*	-5.6882*
	(2.5525)	(2.6875)	(3.1450)	(3.2988)
Boone	0.3247	0.1372	-0.9467	-0.7743
	(0.9225)	(0.8901)	(1.1125)	(1.1183)
Concentration	-	1.5530	-	-1.2420
		(1.2306)		(1.2679)
Observations	803	803	802	802

Note. Table 2.14 uses the same data, variables, and estimation procedures as in Table 2.8 except that it adds the competition variables Lerner and Boone to the respective specifications. Only the competition and concentration coefficients are reported. The values of the control variables across the three panels are identical. The values for H-statistic and Concentration in each of the three panels are the same as in Table 2.8 (refer note there). The values for Lerner and Boone are set as follows: Panel A uses constant values for these variables for the entire time period (1980-2011), where Lerner and Boone are set equal to their average value over the periods for which data are available: i.e.1996-2011 and 1999-2011, respectively. Panel B uses two sets of constant values for each variable. Lerner uses the 1996 value for 1980-1996 and the country average for 1997-2011. Boone uses the 1999 value for 1980-1999, and the country average for 2000-2011. Panel C uses the time-varying values for these variables whenever possible. The Lerner variable uses the 1996 value for 1980-1996 and time-varying values for 1997-2011; while the Boone variable uses the 1999 value for 1980-1999, and time-varying values for 2000-2011. Note that increases in H-statistic are associated with more competition while increases in Lerner and Boone are associated with less competition. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 2.14 repeats the analyses of Table 2.8. The Lerner and Boone variables are added to the respective specifications, while everything else is held constant. Panel A uses constant Lerner and Boone values for the whole period of 1980-2011. Average values for the Lerner and

Boone variables are calculated over the entire period for which data are available. Panel B uses two sets of constant values for Lerner and Boone. The Lerner variable uses the 1996 value for 1980-1996 and the country average for 1997-2011; while the Boone variable uses the 1999 value for 1980-1999, and the country average for 2000-2011. Panel C uses a combination of a constant value and a time varying value. The Lerner variable uses the 1996 value for 1980-1996 and time-varying values for 1997-2011; while the Boone variable uses the 1999 value for 1980-1999, and time-varying values for 2000-2011.

H-statistic is statistically insignificant in all three panels, with the coefficient values for H-statistic being relatively small compared to SCW's reported values. If increased competition is associated with greater financial stability, the estimated coefficient values for Lerner and Boone need to be negative in columns (2) and (3), and positive in columns (6) and (7). In panel A, the estimated coefficients for Lerner and Boone display the correct sign. However, the coefficients for Lerner are not statistically significant. The coefficient for Boone is significant at the five percent significance level only in column (3).

In Panel B, the signs of the coefficients reverse, suggesting that an increase in competition is positively associated with financial fragility, though only one of the estimated coefficients for Lerner (column 3) is significant at the 5 percent level. The results in panel C also show the same signs as in panel B, with none of the coefficients significant at the 5 percent level.

The concentration variable shows statistically significant results in panel A. However the results are puzzling. In column (3), concentration is associated with greater financial stability, while in column (7) concentration is associated with decreased stability. Both of the respective coefficients are statistically significant at the 1 percent level. In panel B the concentration variable is significant at the 10 percent level, and suggests that increased concentration leads to greater stability. In panel C it is insignificant in both columns (3) and (7).

Table 2.15 repeats the analysis of Table 2.9, adding Lerner and Boone variables into the respective specifications, with everything else held constant. The values of H-statistic and Concentration are the same as in Table 2.9. Panel A uses two constant values each for Lerner and Boone: country averages for the periods 1999-2007 and 2008-2015 for each of the variables. Panel B uses the time-varying values of Lerner and Boone throughout the period from 1999 to 2015.

Table 2.15

Replication Using Z-Score as the Dependent Variable and Additional Competition Variables: 1999-2015

Variable	**Panel A: Constant values: two periods**		**Panel B: Mixed constant and time-varying values**	
	(1)	**(2)**	**(3)**	**(4)**
H-statistic	0.0028	-0.0296	-0.1635	-0.1793
	(0.1639)	(0.1613)	(0.1512)	(0.1500)
Lerner	0.0061	0.0142	-0.0680***	-0.0598***
	(0.0235)	(0.0211)	(0.0199)	(0.0208)
Boone	0.1760	0.1262	-0.0035	-0.0252
	(0.1194)	(0.1204)	(0.0659)	(0.0565)
Concentration	-	0.5779***	-	0.5117***
		(0.1409)		(0.1575)
Observations	384	384	376	374
AIC	228.4416	230.1708	223.3076	223.6320
SIC	295.6025	301.2824	290.1106	294.2686

Note. Table 2.15 uses the same data, variables, and estimation method as Table 2.9. The only exception is that it adds the competition variables Lerner and Boone to the respective specifications. The values of the control variables across the panels A and B are identical. Only the competition and concentration coefficients are reported. The values for H-statistic and Concentration in each of the panels are the same as in Table 2.9 (see note there). The values for Lerner and Boone are set as follows. Panel A uses two sets of constant variables for each variable. For both Lerner and Boone, it uses the country average of these variables for the periods 1999-2007 and 2008-2015, respectively. Panel B uses the time-varying values of these variables for the entire period. Note that increases in H-statistic are associated with more competition while increases in Lerner and Boone are associated with less competition. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

The results show that the estimated coefficients of time-varying Lerner are highly significant in columns (3) and (4). The estimated Lerner index coefficients indicate that increased competition contributes to financial stability. The estimated results for Boone are similar to those of Lerner, but the results are statistically insignificant. The estimated coefficients for H-statistic are also statistically insignificant. The results for Concentration remain unchanged with the addition of the Lerner and Boone variables. The estimated coefficients for Concentration are statistically significant in Table 2.15 at the 1 percent level of significance. The estimates indicate that greater concentration is associated with more stability.

2.11 Exclusion of the Global Financial Crisis Period

Calderon and Schaeck (2016) describe the impact of government aid programmes on competition in the banking sector during the Global Financial Crisis (GFC) period. They find that governments supported banks in terms of liquidity support, recapitalizations, and nationalizations. These government aid programmes contributed to an increase in bank competition. Furthermore, they influenced the relationship between competition and stability.

To eliminate the impact of massive bailout programmes, Section 2.11 excludes the GFC period and re-estimates the key models for 1980-2007. Table 2.16 repeats Table 2.8 and restricts the sample period up to 2007. H-statistic is always statistically insignificant. The estimated coefficients for the concentration variable are consistent with a positive association between concentration and financial stability, with all the coefficients being significant at the 5 percent significance level, except in column (7) of panel C.

Table 2.16

Exclude GFC: Replication of Key Models Using Updated Data: 1980-2007

Variable	**Duration models**		**Logit models**	
	(2)	**(3)**	**(6)**	**(7)**
Panel A: Constant H-statistic and Concentration values: whole period				
H-statistic	0.2380	0.1974	-0.0787	-0.0965
	(0.8646)	(0.9241)	(0.8771)	(0.9879)
Concentration	-	4.6680***	-	-4.9014***
		(1.2643)		(1.3642)
Observations	731	731	732	732
Panel B: Constant H-statistic and Concentration values: two periods				
H-statistic	0.2380	0.1819	-0.0787	-0.0311
	(0.8646)	(0.8269)	(0.8771)	(0.8572)
Concentration	-	3.5186***	-	-3.6476***
		(1.2614)		(1.3552)
Observations	731	731	732	732
Panel C: Mixed constant, time-varying H-statistic and Concentration values				
H-statistic	0.2380	0.2620	-0.0787	-0.1105
	(0.8646)	(0.8226)	(0.8771)	(0.8298)
Concentration	-	2.1741**	-	-1.6310
		(1.0443)		(1.0770)
Observations	731	731	732	732

Note. The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722-723). Only the competition and concentration coefficients are reported. All three panels of estimates use multiple sources to achieve maximum number of observations with updated data. The values of the control variables across the three panels are identical. All three panels use SCW's (constant) H-statistic values for the entire period (1980-2007). Three types of Concentration variables used in three panels. Panel A uses SCW's (constant) values for the entire time period (1980-2007). Panel B uses SCW's value for 1980-1995, and the country average of Concentration for 1996-2007. Panel C uses SCW's value for 1980-1995, and time-varying values for 1996-2007. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 2.17

Exclude GFC: Replication of Key Models Using Additional Competition Measures: 1980-2007

Variable	Duration models		Logit models	
	(2)	**(3)**	**(6)**	**(7)**
Panel A: Constant H-statistic and Concentration values: whole period				
H-statistic	-0.6917	-1.2445	0.8503	1.5609
	(1.0783)	(1.3318)	(1.0353)	(1.4064)
Lerner	-5.7805	-7.5604*	5.9823	8.7118*
	(3.5770)	(4.2883)	(3.6883)	(4.6459)
Boone	-0.6347	-1.3263**	0.8414	1.6350
	(0.4270)	(0.6068)	(0.5744)	(1.0072)
Concentration	-	5.6126***	-	-6.1137***
		(1.4553)		(1.6856)
Observations	731	731	732	732
Panel B: Constant H-statistic and Concentration values: two periods				
H-statistic	0.9451	0.7347	0.0283	0.0411
	(1.0818)	(1.0012)	(1.1130)	(1.0648)
Lerner	4.6027	5.0350*	0.8176	0.2620
	(3.1067)	(2.9155)	(4.1400)	(3.8848)
Boone	0.3677	-0.1068	-0.1740	0.3002
	(1.0237)	(1.0166)	(1.1378)	(1.1413)

Variable	Duration models		Logit models	
	(2)	(3)	(6)	(7)
Concentration	-	4.0457***	-	-3.7106***
		(1.5081)		(1.3091)
Observations	731	731	732	732
Panel C: Mixed constant, time-varying H-statistic and Concentration values				
H-statistic	0.3320	0.3409	-0.6194	-0.6367
	(0.9641)	(0.9075)	(1.1315)	(1.0907)
Lerner	0.5535	0.9104	-2.9796	-3.3666
	(2.7448)	(2.9320)	(3.2142)	(3.4332)
Boone	0.1395	-0.1545	-0.6542	-0.3828
	(0.8350)	(0.7558)	(1.0189)	(0.9729)
Concentration	-	2.2978**	-	-1.7974
		(1.1272)		(1.2165)
Observations	731	731	732	732

Note. The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722-723). Only the competition and concentration coefficients are reported. All three panels of estimates use multiple sources to achieve maximum number of observations with updated data. The values of the control variables across the three panels are identical. The values for H-statistic and Concentration in each of the three panels are the same as in Table 2.16 (refer note there). The values for Lerner and Boone are set as follows: Panel A uses constant values for these variables for the entire time period (1980-2007), where Lerner and Boone are set equal to their average value over the periods for which data are available: i.e. 1996-2007 and 1999-2007, respectively. Panel B uses two sets of constant values for each variable. Lerner uses the 1996 value for 1980-1996 and the country average for 1997-2007. Boone uses the 1999 value for 1980-1999, and the country average for 2000-2007. Panel C uses the time-varying values for these variables whenever possible. Lerner uses the 1996 value for 1980-1995 and the time varying values for 1996-2007. Boone uses the 1999 value for 1980-1998, and the time varying values for 1999-2007. Note that increases in H-statistic are associated with more competition while increases in Lerner and Boone are associated with less competition. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 2.17 incorporates the two alternative competition variables, Lerner and Boone, in the estimation equations of Table 2.16. H-statistic is everywhere insignificant. Likewise, Lerner and Boone never achieve statistical significance at the 5 percent level, with one exception (panel A, column 3). Furthermore, the respective coefficients provide conflicting estimates of the relationship between competition and financial stability. In contrast, estimates for the concentration variable confirm previous results and suggest that greater concentration is generally associated with increased stability.

2.12 Conclusion

This chapter provides a comprehensive replication of Schaeck et al. (2009) paper, “Are competitive banking systems more stable?” The replication consists of six steps. Firstly, this chapter re-estimates the results with the authors’ data. The re-estimation results closely match the published estimates of the original. The second step of the replication updates the control variables using multiple data sources. The results of this analysis find that competition, as measured by the H-statistic, is not statistically significant when using more recent data. However, the results for the concentration variable confirm SCW’s conclusion that greater concentration increases financial stability.

Thirdly, this chapter expands the sample period of study. The analysis with the extended sample period considers various aspects: updated data from multiple sources; comparison of the results using constant H-statistic and concentration variables, and time-varying values of H-statistic and Concentration. The results do not support SCW’s conclusions using any of these methods. H-statistic is statistically insignificant and the associated t-statistics decrease substantially from an average of over 2 to less than 1.

Fourthly, the use of Z-score as a stability measure is explored. This chapter finds that both H-statistic and Concentration are statistically insignificant when Z-score is used as the stability measure. The fifth step adds the Lerner index and the Boone indicator as alternative competition measures. The estimated results using these alternative measures of competition are consistent with previous findings of the chapter. However, the associated estimates are statistically insignificant at the 5 percent level in most of the regressions. The concentration variable shows a statistically significant, positive association between concentration and financial stability in 5 out of 8 estimations.

Finally, this chapter removes the effect of the GFC and re-estimates the results. The competition measures are statistically insignificant at the 5 percent level except in one estimation. The concentration variable continues to be positively associated with financial stability.

In summary, this extensive replication of SCW's paper produces a substantial body of evidence that does not support SCW's conclusion that competitive banking systems are more financially stable. However, it does confirm their result that concentration of the banking system is positively associated with stability.

Chapter Three

3.1 Introduction

Competition in the banking system has been a focal point of interest among researchers and policy makers. Some researchers argue that competition contributes to adverse shocks in the financial system while others argue that it is protective against adverse shocks. Theoretical and empirical views on bank competition and financial stability present conflicting views and do not provide clear guidance on the relationship between bank competition and financial stability.

The competition-fragility hypothesis states that greater competition leads to instability of the financial system (Allen & Gale, 2004; Keeley, 1990; Marcus, 1984). It argues that more concentrated and less competitive banking systems are more stable, with the associated profits providing a buffer against financial instability. Greater concentration provides an incentive against excessive risk taking. An alternative view is provided by (Boyd & De Nicolo, 2005). They argue that greater concentration leads to financial instability. With less competition, banks charge firms higher interest rates. Higher borrowing costs make firms financially vulnerable, which in turn increases their default risk. All this feeds back into the banking system in the form of non-performing loans. The empirical evidence is mixed with respect to the two views, so that there is no clear conclusion on the validity of the competition-fragility or competition-stability hypotheses.

Zigraiova and Havranek (2016) conduct a Meta-Regression Analysis (MRA) to bring together the empirical literature on the relationship between bank competition and financial stability. They analyze 598 estimates across 31 studies. Zigraiova and Havranek (Z&H hereafter) find evidence of publication bias. After they control for publication bias, they estimate an economically insignificant relationship between competition in the banking sector and financial stability.

The purpose of this chapter is to perform a pure replication and a verification of Zigraiova and Havranek (2016) Journal of Economic Survey paper, “Bank Competition and Financial Stability: Much Ado about Nothing?” The pure replication uses the same data and code that Z&H used for their paper, having posted it at the website: http://meta-analysis.cz/competition/. The aim of the pure replication is to verify that their data and code produce the estimates reported in their paper. The verification exercise is different in that it goes back to the original studies and recodes the variables. The aim of the verification is to investigate the degree to which coding subjectivity affects the results. It checks whether independent coders would produce data that allows one to confirm Z&H’s empirical conclusions.

This chapter finds that the pure replication results closely match Z&H’s estimates. There is a very small effect associated with bank competition on financial stability, and it is statistically insignificant. It also finds evidence of publication bias, with journals seemingly preferring to publish estimates supporting the competition-fragility hypothesis. Data re-coding produced some differences, mainly in the categorizations of the countries included in the respective studies. This affected the associated calculation of partial correlation coefficients, which produced slightly different results. However, in the end, the results support Z&H’s conclusion that there is only a small effect from bank competition on financial stability. Subsequent robustness checks also find publication bias in the literature and confirm the baseline conclusion.

This chapter is organized as follows. Section 3.2 explains the dataset. Section 3.3 discusses the replication procedure and Section 3.4 explains the heterogeneity in the literature.

Section 3.5 applies Bayesian Model Averaging to handle model uncertainty. Section 3.6 calculates best practice estimates for the competition-stability hypothesis. Section 3.7 undertakes robustness checks. Section 3.8 discusses some corrections to the estimates. Section 3.9 re-estimates the effect of competition-stability omitting quadratic effects, and Section 3.10 summarizes the conclusions.

3.2 The Dataset of Competition-Stability Estimates

Z&H collected 598 estimates from published and unpublished studies. They searched for relevant studies with the Google Scholar and RePEC search engines, using different combinations of the following four keyword pairs: Competition-Stability, Competition-Fragility, Concentration-Stability and Concentration-Fragility (Zigraiova & Havranek, 2016).

The literature uses a variety of measures for competition. Some measures are increasing in greater competition, and others decrease as competition increases. For example, a large concentration ratio indicates less competition, while a large H-statistic value indicates high competition. The same issues arise with measures of financial stability. A large value of Z-score indicates high stability, while a large value of the non-performing loan ratio indicates less stability. As a result, the sign of the coefficient estimate needs to be adjusted to reflect the relationship between bank competition and stability.

To assess the strength and relationship of the competition-stability estimates, Z&H transformed all the reported estimates into partial correlation coefficients (PCCs). The partial correlation coefficient measures the correlation between dependent and independent variable, holding all other variables constant. That is, the effects of all other factors are partialled out, leaving only the contribution of the independent variable (Doucouliagos, 2011). The formulas of PCC and standard error of PCC (SEPCC) are as follows:

$$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}}, \quad (3.1)$$

$$SEPCC_i = \sqrt{\frac{1 - PCC_i^2}{df_i}}, \quad (3.2)$$

where t is the t-statistic of the estimated coefficient, df is the degrees of freedom of the estimation, and i identifies the i^{th} estimated coefficient.

3.3 Pure Replication vs. Verification

Pure replication uses data and codes published by Z&H to mimic their analysis step by step. Part of their STATA code used to produce tables and figures is available at the website: http://meta-analysis.cz/competition/. This replication exercise uses their codes to reproduce Table 3.1 to Table 3.5.1. The code for the remaining tables was unavailable at the website and had to be written based on the description given in the paper[9].

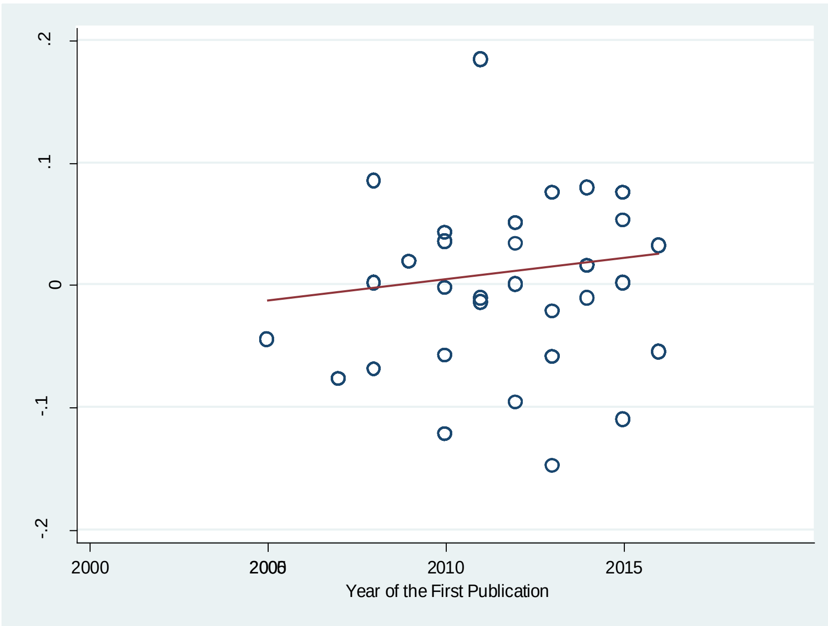
In verification (as opposed to pure replication) the same 31 studies are re-coded. Z&H collect 35 variables from each study. This chapter collects 33 variables from the original 31 studies and takes two variables from Z&H's dataset. Z&H collected their recursive impact factor values and number of citations in July 2014 and the current value of these variables are different from the original case. Therefore, this chapter uses the same recursive impact factor values and number of citations used by Z&H.

[9] Data and codes to replicate all the results of the chapter can be downloaded from https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/1FYHUZ or https://github.com/SamangiBandaranayake/Bank-Competition-and-Financial-Stability/tree/master/Chapter%20Three

3.3.1 Diversity of the estimated competition coefficient

There is substantial heterogeneity of estimates in the literature on banking competition and financial stability, with no evidence of convergence in studies over time. Figure 3.1 shows the median PCCs corresponding to the estimated effects of bank competition on financial stability reported in individual studies. The horizontal axis presents the year when the study first appeared in Google Scholar. Figure 3.1A is based on Z&H's dataset, while Figure 3.1B uses the re-coded data from the verification exercise. Figures 3.1A and 3.1B both present a similar pattern. The regression lines show an upward linear trend in both figures.

A



B

Figure 3.1A: The Median PCC Estimates of Bank Competition and Financial Stability
Note. The median PCC values are taken from the data published by Zigraiova and Havranek (2016).

Figure 3.1B: The Median PCC Estimates of Bank Competition and Financial Stability
Note. The median PCC values are calculated from the re-coded data.

A

B

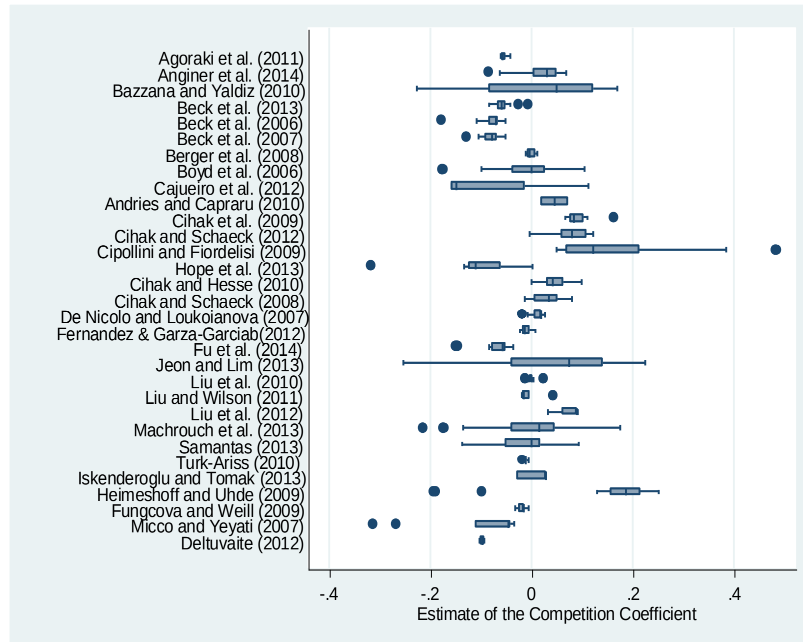


Figure 3.2A: Variability in the Estimated Competition Coefficients across Individual Studies

Note. The figure shows a box plot of the PCCs of the competition coefficient estimates from the data published by Zigraiova and Havranek (2016).

Figure 3.2B: Variability in the Estimated Competition Coefficients across Individual Studies

Note. The figure shows a box plot of the PCCs of the competition coefficient estimates from the re-coded data.

Figures 3.2A and 3.2B show forest plots of the PCCs of competition coefficient estimates reported in 31 studies. Figure 3.2A is produced from the authors' data, while Figure3.2B is based on the re-coded data. There is a wide dispersion, both within and between studies in Figures 3.2A and 3.2B. Note that the coding differences have produced some differences. For example, "Study ID-13" examines the impact of bank concentration on financial stability. The finding of this study suggests that there is a positive effect from bank concentration on fragility. Coders of MRA should code this as competition leads to stability. Z&H coded "Study ID-13" as competition leads to fragility. This reverses the direction of the plot.

Table 3.1

Estimates of the Competition Effect for Different Country Groups

Country Group	Unweighted			Weighted			No of estimates
	Mean	95% CI		Mean	95% CI		
Panel A							
All	−0.001	−0.025	0.023	−0.012	−0.035	0.011	598
Developed	0.020	−0.032	0.073	0.011	−0.030	0.052	201
Developing and transition	0.001	−0.022	0.023	−0.019	−0.051	0.012	194
Panel B							
All	0.009	-0.015	0.033	-0.001	-0.025	0.023	598
Developed	0.025***	0.007	0.043	0.020**	0.003	0.038	149
Developing and transition	0.006	-0.023	0.035	-0.012	-0.054	0.030	154

Note. The table presents the mean PCCs of competition coefficient estimates for all estimates, estimates from developed (OECD) countries, and developing and transition (non-OECD) countries. The left side of the table presents unweighted mean values and 95% confidence intervals. The confidence intervals around the mean are constructed using standard errors clustered at the study level. On the right side of the table, estimates are weighted by the inverse number of estimates per study. Panel A presents PCC estimates from the data published by Zigraiova and Havranek (2016). Panel B presents PCC estimates from the re-coded data. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 3.1 presents estimates of the competition effect for three groups of estimators. Panel A is a pure replication from Z&H's data. Panel B uses data from re-coding. In both panels, the first row presents the effect for all 598 estimates and the second and third rows show the effect for two subgroups: developed countries (member countries of the Organization for Economic Corporation and Development- "OECD") and developing and transition countries (non-OECD countries).

In panel A, there are 201 estimates from developed countries and 194 estimates from developing and transition countries, with the remaining 203 estimates belonging to a mixed category of developed, developing and transition countries. Panel B reports 149 estimates from developed countries and 154 estimates from developing and transition countries. The verification exercise identified differences in country categorization. For example, Albania, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Serbia, Slovakia and Slovenia are included in "Study ID-1" for the sample period 1998-2005. Z&H coded "Study ID-1" under the group of non-OECD countries. However, Czech Republic, Hungary, Poland, and Slovakia were OECD members during the sample period of the study. Therefore, "Study ID-1" should be classified as belonging to the mixed category. Due to such differences, the mean values of the PCCs and 95% confidence intervals are somewhat different in panels A and B.

Table 3.1 reports unweighted and weighted mean values of PCCs and 95% level confidence intervals. The weighted estimates weight the respective estimates using the inverse of the number of estimates reported per study. This serves to assign approximately the same weight to all studies even though some studies have more estimates than others. This gives equal importance to each study of the selected sample and eliminates selection bias (Mansournia & Altman, 2016).

The unweighted and weighted mean values of PCCs in panels A and B are close to zero. As per the guidelines for the interpretation of PCCs published by (Doucouliagos, 2011), when the effect size is less than 0.07 it is considered to be a small effect. The estimated, overall effect for all 598 estimates in panel A indicates that competition is negatively associated with financial stability, but the effect size is small (< 0.07). Further, the effect size is statistically insignificant for all three groups in panel A.

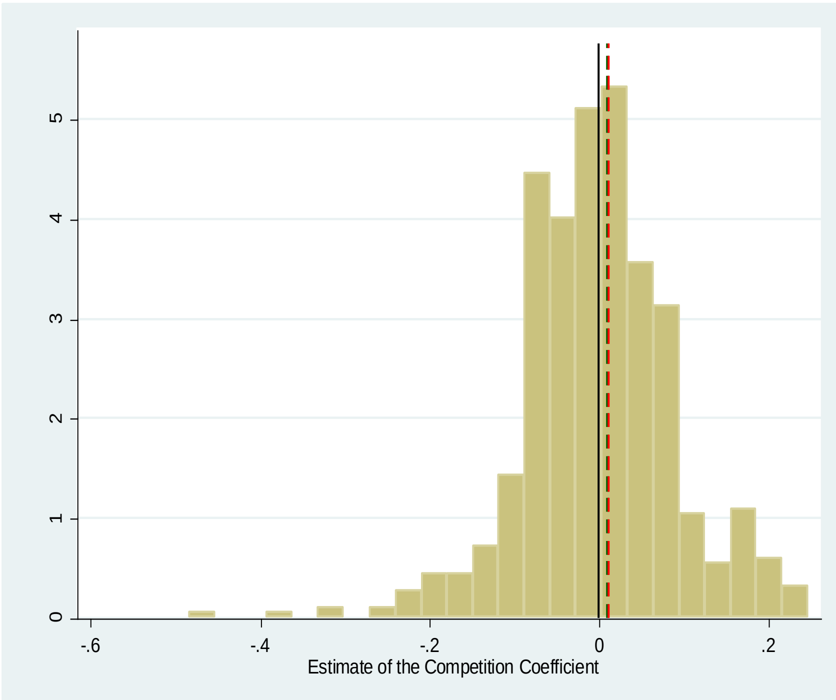
The results are slightly different in panel B. The unweighted mean values of the PCC estimates competition to be positively associated with financial stability. The weighted mean values of the PCCs show competition to negatively influence stability for all estimates, and for estimates from developing and transition countries. Panel B reports statistically significant effect sizes at the 5 percent level for the developed country category.

Figure 3.3A presents the distribution of PCCs for the full set of competition coefficient estimates. The PCCs are symmetrically distributed around zero with a mean value of -0.0009. The median PCC value is 0.0010. There are 21 published studies, with 376 estimates from these published studies. The mean value of the PCC from published estimates is 0.0116. This indicates that published studies report slightly larger estimates compared to unpublished studies.

Figure 3.3B also displays a symmetric distribution around zero. The distribution of PCCs ranges from -0.3168 to 0.4835. The solid vertical line (PCC = 0.0090) denotes the mean of all PCCs. The dashed lines denote the mean of the median PCCs as 0.0179. The mean PCC value for estimates reported in studies published in peer-reviewed journals is 0.0120.

Figures 3.3A and 3.3B are similar but not identical due to coding differences. The mean value of PCCs in Figure 3.3A is -0.0009, while it is 0.0090 in Figure 3.3B. There is a 0.0108 (0.0090-(-0.0009)) difference in mean values for all estimates in Figures 3.3A and 3.3B. Likewise, there are differences in median and mean PCC values for the published studies. These differences occur as a result of differences in estimated PCCs arising from recoding the data. However, the differences are small.

A **B**



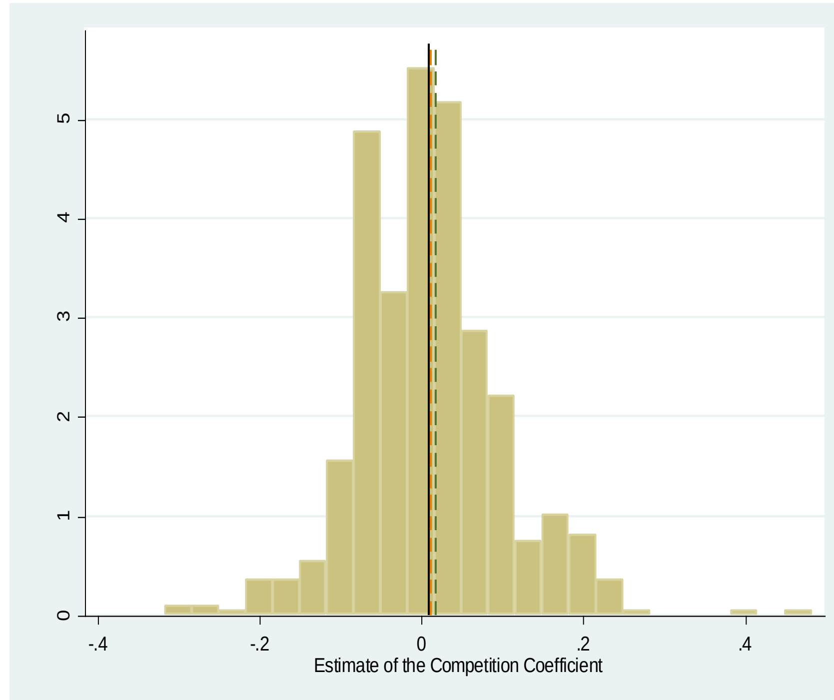


Figure 3.3A: The Distribution of PCC Estimates

Note. The figure shows a histogram of the PCCs of the competition coefficient estimates from the data published by Zigraiova and Havranek (2016). The solid vertical line (black line) denotes the mean of all the PCCs. The dashed lines denote the mean of the median PCCs of all estimates (green dash line) and the mean of the PCCs of published studies (red dash line).

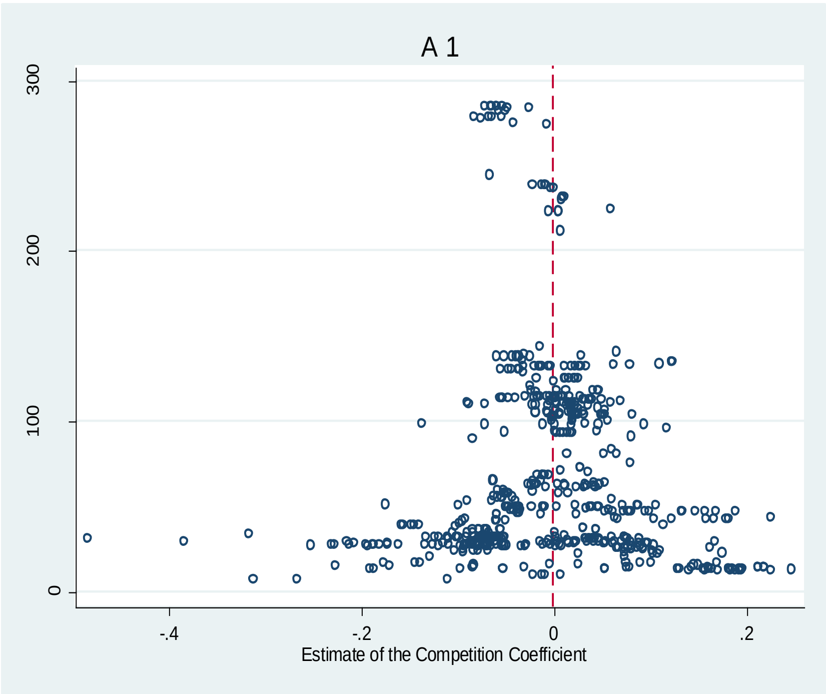
Figure 3.3B: The Distribution of PCC Estimates

Note. The figure shows a histogram of the PCCs of the competition coefficient estimates from the re-coded data. The solid vertical line (black line) denotes the mean of all the PCCs. The dashed lines denote the mean of the median PCCs of all estimates (orange dash line) and the mean of the PCCs of published studies (green dash line).

3.3.2 Testing for publication bias

Doucouliagos and Stanley (2013) find publication bias in empirical studies. Publication bias arises when the probability of publishing an estimate depends on its sign or statistical significance. Funnel plots are commonly used to assess publication bias. When the funnel plot is asymmetrical, publication bias is likely (Egger, Smith, Schneider, & Minder, 1997).

Figure 3.4 shows four funnel plots of PCC estimates. These are all symmetrical, suggesting the absence of publication bias. Funnel plots 3.4A1 and 3.4B1 present individual PCC values for all competition coefficient estimates. Funnel plots 3.4A2 and 3.4B2 present study median PCC values. Figure 3.4As are produced from Z&H’s data and Figure 3.4Bs are from the re-coded.



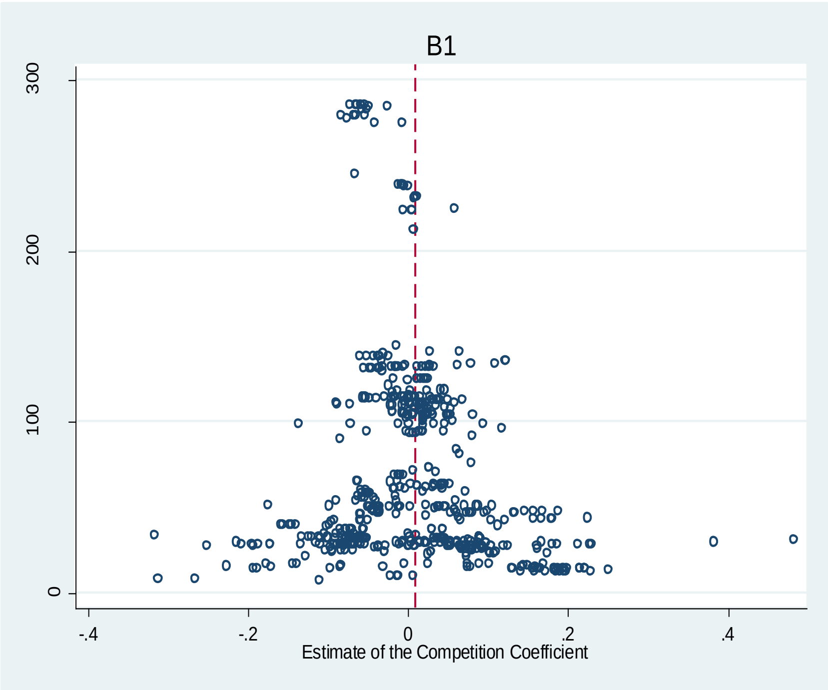
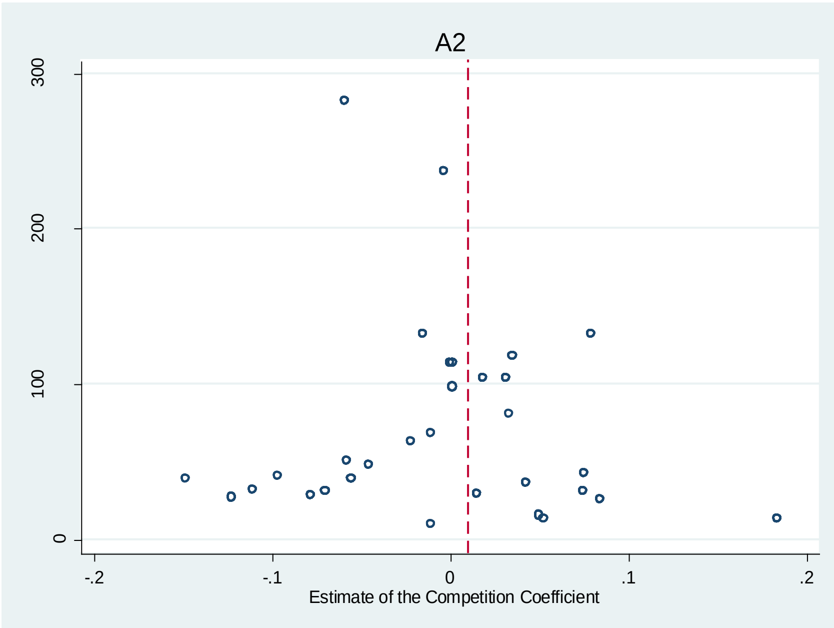


Figure 3.4A1: PCC of All Estimates
Note. The figure shows a funnel plot of the PCCs of the competition coefficient estimates from the data published by Zigraiova and Havranek (2016). The dashed vertical line denotes the mean value the PCC of all the estimates.

Figure 3.4B1: PCC of All Estimates
Note. The figure shows a funnel plot of the PCCs of the competition coefficient estimates from the re-coded data. The dashed vertical line denotes the mean value the PCC of all the estimates.



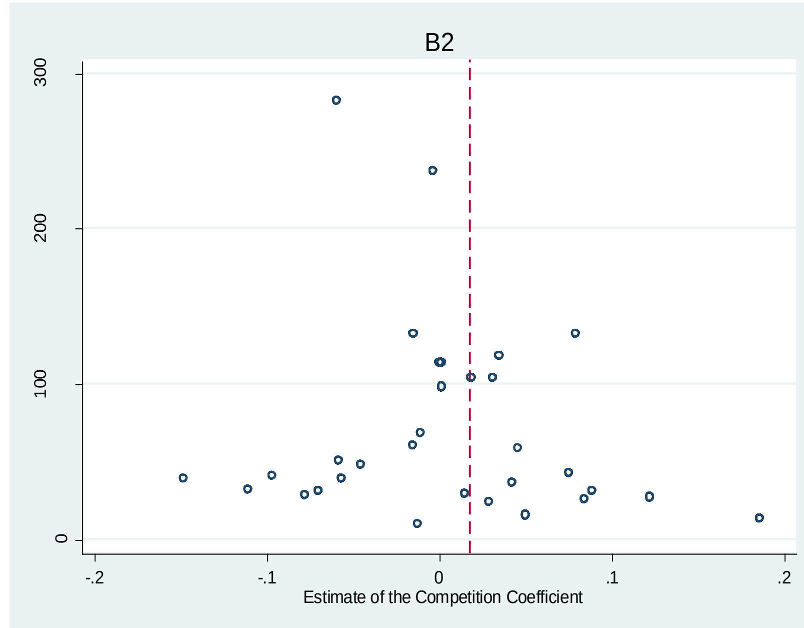


Figure 3.4A2: Median Values of PCC Estimates
Note. The figure shows a funnel plot of the median values of PCCs of the competition coefficient estimates from the data published by Zigraiova and Havranek (2016).The dashed vertical line denotes the mean value the median PCC of all the estimates.

Figure 3.4B2: Median Values of PCC Estimates
Note. The figure shows a funnel plot of the median values of PCCs of the competition coefficient estimates from the re-coded data. The dashed vertical line denotes the mean value the median PCC of all the estimates.

3.3.3 Funnel asymmetry tests

The Funnel Asymmetry Test (FAT) is another technique used to explore publication bias. The FAT examines the relationship between coefficient estimates and their standard errors. When there is no publication bias, there is no correlation between the coefficient of estimates (PCC) and their standard errors (Doucouliagos & Stanley, 2013; Egger et al., 1997; Stanley, 2007). The equation for the FAT test is as follows;

$$PCC_i = \beta_0 + \beta_1 SE\ (PCC)_i + \varepsilon_i \ , \tag{3.3}$$

Where PCC_i is the partial correlation coefficient of the competition coefficient, $SE\ (PCC)_i$ is the standard error of the PCC, β_0 is the mean PCC corrected for publication bias, $\beta_1$is the degree of publication bias, and ε_i is the error term.

Table 3.2 presents the result of the FAT. Panel A is a pure replication from Z&H's data and Panel B is a verification of Z&H's results based on re-coded data. In both panels, unweighted regression results are reported at the top, and weighted regressions (by inverse of number of estimates per study) are reported at the bottom. The FAT results are presented for two groups. One group considers all estimates and the other group considers estimates from published studies. Fixed effects estimation and instrumental variable estimation techniques are considered for the assessment. The null hypothesis for the FAT is $\beta_1 = 0$. Panels A and B reject the null hypothesis that there is no publication bias at the 1 percent and 5 percent levels of significance. As per the guideline of (Doucouliagos & Stanley, 2013):

- β_1 is statistically significant and within the range of $1 \leq |\beta_1| \leq 2,$ there is a substantial selectivity

- β_1 is statistically significant and $|\beta_1| > 2$, there is severe selectivity.

Accordingly, panels A and B indicate a substantial degree of selectivity. The instrumental variable estimates for published studies indicate severe selectivity. The negative coefficients suggest that sample selection favors negative estimated effects of competition and financial stability. The effect after controlling for publication bias (β_0) is close to zero.

Table 3.2

Funnel Asymmetry Tests

Panel A				
Unweighted Regressions	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
SE (publication bias)	-1.671**	-1.898**	-1.614***	-2.291***
Constant (effect beyond bias)	0.044**	0.073**	0.043***	0.086***
No of estimates	598	376	598	376
No of studies	31	21	31	21
Weighted Regressions	**FE**	**FE_Published**		
SE (publication bias)	-1.568***	-1.636***		
Constant (effect beyond bias)	0.034***	0.044***		
No of estimates	598	376		
No of studies	31	21		

Panel B				
Unweighted Regressions	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
SE (publication bias)	-1.744**	-1.859**	-1.561***	-2.218***
Constant (effect beyond bias)	0.055***	0.071**	0.050***	0.083***
No of estimates	598	376	598	376
No of studies	31	21	31	21
Weighted Regressions	**FE**	**FE_Published**		
SE (publication bias)	-1.625***	-1.619***		
Constant (effect beyond bias)	0.045***	0.041***		
No of estimates	598	376		
No of studies	31	21		

Note. The table presents the results of FAT. Panel A presents FAT results from the data published by Zigraiova and Havranek (2016). Panel B presents FAT results from the re-coded data. The standard errors are clustered at the study level. Panels A and B present unweighted and weighted regressions. Fixed effects estimation technique used study dummies and instrumental variable estimation technique used the logarithm of the number of observations as the instrumental variable. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

In Table 3.2, $SE\ (PCC)_i$ measures the standard error of the estimated PCC_i. As different estimated PCCs have different standard errors, it follows that the error term suffers from heteroscedasticity. To correct this, equation (3.3) is divided by $SE\ (PCC)_i$ to enable a weighted least squares estimate of the respective parameters (Stanley, 2007). This transformation creates the following new equation:

$$t_i = \beta_1 + \beta_0 \left(1/SE(PCC_i)\right) + \mu_i \,, \tag{3.4}$$

where t_i is the t-statistic, β_0 is the mean PCC corrected for publication bias, and β_1 measures the degree of publication bias.

Table 3.3 presents heteroscedasticity-corrected FAT results. Panel A shows results using Z&H’s dataset, with panel B showing results using the re-coded data. In each panel, regressions weighted by PCC precision are reported on top, and regressions weighted by both precision and the inverse of the number of estimates per study are reported at the bottom. FAT results are presented for two groups. One group considers all estimates, and the other group considers estimates from just published studies. Fixed effects estimation and instrumental variable estimation techniques are used. The null hypothesis of the FAT is $\beta_1 = 0$.

Panels A and B reject the null hypothesis of no publication bias in most cases, with estimates suggesting the presence of moderate publication bias. The presence of publication bias is strong in published studies compared to unpublished studies. Overall, there is evidence of negative publication bias, suggesting that journals are favorable towards results supporting the competition-fragility hypothesis. Both panels show the bias-corrected effect (“effect beyond bias”, cf. 1/SE) is less than 0.07. Except for the first column, most results are statistically significant at the 10 percent level.

Table 3.3

Heteroscedasticity-Corrected Funnel Asymmetry Tests

		Panel A		
Weighted by precision	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
1/SE (effect beyond bias)	0.005	0.065	0.019**	0.053***
Constant (publication bias)	-0.757	-4.000*	-1.706**	-3.344***
No of estimates	598	376	598	376
No of studies	31	21	31	21
Weighted by precision and No. of observations	**FE**	**FE_Published**		
1/SE (effect beyond bias)	0.013	0.056**		
Constant (publication bias)	-1.539**	-4.339**		
No of estimates	598	376		
No of studies	31	21		
		Panel B		
Weighted by precision	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
1/SE (effect beyond bias)	0.005	0.062	0.018*	0.050***
Constant (publication bias)	-0.491	-3.833	-1.343**	-3.152***
No of estimates	598	376	598	376
No of studies	31	21	31	21

Weighted by precision and No. of observations	FE	FE_Published
1/SE (effect beyond bias)	0.013	0.054*
Constant (publication bias)	-1.251	-4.190**
No of estimates	598	376
No of studies	31	21

Note. The table presents the results of heteroscedasticity-corrected FAT. Panel A presents heteroscedasticity corrected FAT results from the data published by Zigraiova and Havranek (2016). Panel B presents heteroscedasticity corrected FAT results from the data re-coding. The standard errors are clustered at the study level. Fixed effects estimation technique used study dummies and instrumental variable estimation technique used the logarithm of the number of observations as the instrumental variable. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

3.4 Heterogeneity

To explain the heterogeneity of estimated effects, 35 variables representing a number of study and estimate characteristics were coded from the original studies. Variable definitions are given in Appendix 2. In Table 3.4, panel A describes summary statistics of the variables from Z&H's dataset, and panel B presents summary statistics of variables from the re-coded data. Panels A and B reports three figures: mean, standard deviation, and mean weighted by the inverse number of estimates reported per study. All variables are classified into eight groups: data characteristics, countries examined, design of the analysis, treatment of stability, treatment of competition, estimation method, control variables, and publication characteristics (Zigraiova & Havranek, 2016).

Group 1: Data characteristics

Data characteristics include PCCs, standard errors of PCCs, the logarithm of the number of observations used in the regression, the logarithm of the number of years (in the sample period), and the mean year of the sample period. The main difference in panels A and B is the mean value of PCCs. Z&H's dataset has a negative mean value of -0.001, while the re-coded data has a positive mean value of 0.009.

Group 2: Countries examined

To address the diversity of countries included in study samples, three dummies are included as developed (OECD) countries, developing and transition (non-OECD) countries, and a mixed category which includes studies with both OECD and non-OECD countries. Panel A reports that approximately 33 percent of estimates are from each country group. Panel B reports 50 percent of the estimates are from the mixed category of OECD and non-OECD countries, 25 percent of the estimates are from the group of developed countries, and 26 percent are from the group of developing and transition countries. This difference in country categorizations was probably the biggest difference discovered during the verification exercise.

Group 3: Design of the analysis

The original studies differed in their estimation designs. This is captured by four dummy variables. Some studies estimate a nonlinear relationship between competition and stability. This is represented by the "quadratic" dummy. 12 percent of the total estimates are nonlinear estimates. Another dummy variable identifies if a study addresses the issue of endogeneity. A majority of estimates address endogeneity: 64 percent in panel A and 57 percent in panel B. The dummy variable "Macro" equals 1 if the competition-stability regression is estimated based on aggregated, country-level data. The variable "Averaged" equals 1 if the competition-stability regression is estimated based on country-level data, but the country-level indicators are calculated as the average of bank-level data.

Group 4: Treatment of stability

Many different measures of financial stability exist. Seven dummy variables are used to capture the most common measures of stability. Z-score is a popular measure, with 45 percent of estimates using this measure of stability. Fourteen percent of the estimates use a crisis dummy as the dependent variable. All the other measures accounts for less than 10 percent of the total estimates.

Group 5: Treatment of competition

Five dummy variables are included to represent the use of different measures of competition. The Lerner index is the most commonly used competition measure, with 36 percent of estimates using this measure. The Herfindahl-Hirschman Index (HHI) is the next most commonly used measure, accounting for 27 percent of total estimates.

Group 6: Estimation method

Studies use a large number of different estimation procedures in estimating the relationship between competition and financial stability. This is captured by six different dummy variables for logit, Ordinary Least Squares (OLS), fixed effects, random effects, generalized method of moments, and two-stage least squares estimations. More than 20 percent of the estimates used (panel) fixed effects estimation method.

Group 7: Control variables

When estimating the competition-stability relationship, studies use a variety of control variables. Three common types of control variables are controls for the regulatory and supervisory environment, the type of ownership of the bank, and the macroeconomic condition of the country. Panels A and B reveal that researchers commonly control for macroeconomic conditions when estimating the relationship between competition and stability.

Group 8: Publication characteristics

The number of citations, the year when the study first appeared in Google Scholar, the recursive impact factor values from RePEc, and whether the study is published in a peer-reviewed journal are all used to capture the publication quality of the study.

Table 3.4

Summary Statistics of Regression Variables

	Panel A			Panel B		
Variable	**Mean**	**SD**	**WMean**	**Mean**	**SD**	**WMean**
Data characteristics						
PCC	-0.001	0.090	-0.012	0.009	0.090	-0.001
SEPCC	0.027	0.022	0.029	0.027	0.021	0.028
Samplesize	7.835	1.615	7.760	7.844	1.598	7.776
T	2.224	0.743	2.264	2.183	0.754	2.212
Sampleyear	8.889	4.328	9.340	9.253	4.440	9.739
Countries examined						
Developed	0.336	0.473	0.366	0.249	0.433	0.275
Developing and transition	0.324	0.469	0.376	0.258	0.438	0.247
Reference case: mixed	0.339	0.474	0.258	0.493	0.500	0.479
Design of the analysis						
Quadratic	0.119	0.324	0.217	0.120	0.326	0.218
Endogeneity	0.635	0.482	0.713	0.574	0.495	0.692
Macro	0.256	0.437	0.133	0.171	0.376	0.140
Averaged	0.120	0.326	0.085	0.027	0.162	0.056
Treatment of stability						
Dummies	0.142	0.349	0.129	0.142	0.349	0.129

	Panel A			Panel B		
Variable	**Mean**	**SD**	**WMean**	**Mean**	**SD**	**WMean**
NPL	0.050	0.218	0.095	0.050	0.218	0.095
Z_score	0.452	0.498	0.537	0.452	0.498	0.537
Profit volatility	0.075	0.264	0.039	0.075	0.264	0.039
Profitability	0.043	0.204	0.045	0.043	0.204	0.045
Capitalization	0.069	0.253	0.040	0.069	0.253	0.040
DtoD	0.065	0.247	0.047	0.065	0.247	0.047
Reference case: other stability	0.104	0.305	0.069	0.104	0.305	0.069
Treatment of competition						
H-statistic	0.090	0.287	0.098	0.090	0.287	0.098
Boone	0.075	0.264	0.108	0.075	0.264	0.108
Concentration	0.157	0.364	0.147	0.159	0.366	0.148
Lerner	0.360	0.480	0.414	0.360	0.480	0.414
HHI	0.266	0.442	0.197	0.266	0.442	0.197
Reference: other competition	0.052	0.222	0.037	0.050	0.218	0.035
Estimation method						
Logit	0.172	0.378	0.161	0.172	0.378	0.161
OLS	0.137	0.344	0.115	0.166	0.372	0.138
FE	0.229	0.421	0.136	0.251	0.434	0.163
RE	0.067	0.250	0.043	0.072	0.259	0.050
GMM	0.182	0.386	0.309	0.167	0.373	0.295

	Panel A			Panel B		
Variable	**Mean**	**SD**	**WMean**	**Mean**	**SD**	**WMean**
TSLS	0.149	0.356	0.110	0.122	0.328	0.077
Reference: other method	0.064	0.244	0.126	0.050	0.218	0.115
Control variables						
Regulation	0.239	0.427	0.282	0.237	0.426	0.272
Ownership	0.166	0.372	0.271	0.186	0.389	0.289
Global	0.794	0.405	0.764	0.844	0.363	0.781
Publication characteristics						
Citations	2.045	1.222	1.790	2.045	1.222	1.790
Firstpub	6.453	2.979	6.677	6.406	3.034	6.677
IFrecursive	0.243	0.210	0.205	0.243	0.210	0.205
Reviewed journal	0.629	0.484	0.677	0.629	0.484	0.677

Note. The table presents summary statistics of regression variables. Panel A presents summary statistics from data published by Zigraiova and Havranek (2016). Panel B presents summary statistics from data re-coding. SD is the standard deviation and WMean is the mean weighted by the inverse of the number of estimates reported per study.

3.5 Results of Bayesian Model Averaging

Table 3.4 gives a sense of the heterogeneity in the literature. Researchers use various dependent and explanatory variables when examining the relationship between bank competition and financial stability. This leads to model uncertainty. Z&H used Bayesian Model Averaging (BMA) to handle the model uncertainty problem. There are 35 explanatory variables. BMA runs multiple regressions with different subsamples of the 2^{35} possible combinations of explanatory variables.

BMA calculates a posterior mean and a posterior standard deviation by weighting each model by its relative likelihood. It also calculates the posterior inclusion probability (PIP). The PIP indicates the probability of a specific variable being included in the true model. Eicher, Papageorgiou, and Raftery (2011) provide specifics on BMA and the strength of the variable's effect based on the PIP value. The effect is considered to be a weak effect when the PIP lies within the range of 0.5 to 0.75, substantial when the PIP is between 0.75 to 0.95, strong when the PIP is between 0.95 to 0.99, and extremely strong when the PIP exceeds 0.99.

Table 3.5.1 presents the results of the BMA analysis. The analysis uses the weighted estimates (by inverse number of estimates per study). Z&H employed Zellner's g-prior for the "unit information prior". This is the default option for the BMA program (Zeugner & Feldkircher, 2015). For a model prior, Z&H chose "uniform". This assigns a uniform model prior for the BMA exercise (Zeugner & Feldkircher, 2015). Table 3.5.1 uses Z&H's data to reproduce the results. The right side of Table 3.5.1 reports regression results of OLS estimation. The OLS estimation includes 15 variables in the estimation equation. These 15 variables were selected because they were calculated to have PIPs greater than 0.5 in the BMA analysis. The results of Table 3.5.1 show that the estimated coefficients are similar in sign and size for both the BMA and OLS estimation procedures.

Table 3.5.1 organizes the diversity of the competition coefficient estimates by categorizing the variables into eight groups. The estimated coefficient of SEPCC (the publication bias variable) is negative and confirms the previous result that researchers prefer to publish results supporting the competition-fragility hypothesis. The associated PIP value is 1.000. The size of the sample is another important determinant, with larger samples estimated to reduce the size of the competition PCC by 0.037. The competition PCCs are also affected by the countries included in the study. Studies with developed countries (OECD countries) or developing and transition (non-OECD countries) are estimated to have larger PCCs than studies that use mixed samples. The largest PCCs are associated with studies using OECD countries.

Literature suggests that the relationship between competition and stability may be non-linear (Agoraki et al., 2011; Fernandez & Garza-Garciab, 2012; Jeon & Lim, 2013). BMA indicates that PCC values derived from quadratic estimates are 0.05 smaller than those from linear estimates. Among the various measures of stability, there is a high PIP value when a dummy variable is used to measure a financial crisis. Other measures of stability have small PIPs. When a dummy variable is used to measure financial stability, it increases the PCC value by 0.21.

Among competition measures, H-statistic and the Boone indicator have high PIP values. Studies that use H-statistic are estimated to produce the largest PCC values. The estimation indicators for logit and OLS both have PIP values greater than 0.50. Logit and OLS estimations are estimated to produce smaller (more negative) estimates of the relationship between competition and stability than other estimation methods. Studies that include regulatory controls estimate smaller competition effects than those that don't. With respect to publication characteristics, number of citations, recursive impact factor, year of first publication, and reviewed journal all have PIPs in excess of 0.50. All but the last are associated with smaller PCC estimates.

The results of OLS estimation are similar to the results of the BMA exercise. All the coefficient values are statistically significant at the 5 percent level, except the coefficient values for the standard error of the PCC and the dummy variable indicating that the study was published in a peer-reviewed journal.

Table 3.5.1

Heterogeneity in the Estimates of the Competition Coefficient

Response variable:	**Bayesian model averaging**			**OLS**		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-1.7883	0.2046	1.000	-1.194	0.651	0.067
Samplesize	-0.0367	0.0035	1.000	-0.024	0.009	0.007
T	0.0005	0.0039	0.052			
Sampleyear	0.0000	0.0005	0.046			
Countries examined						
Developed	0.2015	0.0219	1.000	0.176	0.029	0.000
Developing and transition	0.1072	0.0169	1.000	0.099	0.026	0.000
Design of the analysis						
Quadratic	-0.0533	0.0214	0.997	-0.044	0.013	0.001

Response variable:	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Endogeneity	0.0100	0.0212	0.237			
Macro	0.0025	0.0124	0.070			
Averaged	-0.0004	0.0047	0.040			
Treatment of stability						
Dummies	0.2115	0.0282	1.000	0.184	0.019	0.000
NPL	0.0020	0.0060	0.132			
Z_score	-0.0005	0.0027	0.063			
Profit volatility	0.0006	0.0051	0.037			
Profitability	-0.0003	0.0030	0.035			
Capitalization	0.0001	0.0029	0.027			
DtoD	-0.0013	0.0078	0.050			
Treatment of competition						
H-statistic	0.1083	0.0217	1.000	0.114	0.018	0.000
Boone	-0.0709	0.0313	0.897	-0.058	0.023	0.010
Concentration	-0.0815	0.0226	0.474			
Lerner	0.0036	0.0130	0.122			
HHI	0.0023	0.0108	0.085			
Estimation method						
Logit	-0.1874	0.0230	1.000	-0.160	0.019	0.000
OLS	-0.0352	0.0244	0.756	-0.038	0.018	0.038
FE	0.0113	0.0211	0.277			
RE	0.0018	0.0115	0.058			
GMM	-0.0003	0.0029	0.040			
TSLS	-0.0001	0.0030	0.032			

Response variable:	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Control variables						
Regulation	-0.0321	0.0197	0.798	-0.036	0.014	0.010
Ownership	-0.0147	0.0175	0.481			
Global	-0.0017	0.0058	0.116			
Publication characteristics						
Citations	0.0497	0.0092	1.000	0.046	0.009	0.000
Firstpub	0.0219	0.0044	1.000	0.023	0.003	0.000
IFrecursive	0.1060	0.0528	0.875	0.096	0.048	0.000
Reviewed journal	-0.0249	0.0186	0.725	-0.015	0.014	0.289
Constant	-0.0004	NA	1.000	-0.118	0.086	0.169
Studies			31			31
Observations			598			598

Note. The table presents BMA results and OLS estimation from data published by Zigraiova and Havranek (2016). Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. OLS estimation includes explanatory variables with PIP greater than 0.5. The standard errors are clustered at the study level. The inverse number of estimates per study is taken as the weight.

Table 3.5.2

Verification of the Heterogeneity in the Estimates of the Competition Coefficient

Response variable	**Bayesian model averaging**			**OLS**			**OLS (Z&H's variable selection criteria)**		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Data characteristics									
SEPCC	-1.8207	0.1947	1.0000	-1.4576	0.8458	0.085	-1.3625	0.9114	0.135
Samplesize	-0.0367	0.0051	1.0000	-0.0290	0.0143	0.042	-0.0258	0.0150	0.085
T	0.0006	0.0039	0.0615						
Sampleyear	0.0034	0.0024	0.7402	0.0033	0.0034	0.324			
Countries examined									
Developed	0.0505	0.0091	0.9997	0.0528	0.0212	0.013	0.0678	0.0292	0.020
Developing and transition	-0.0012	0.0062	0.0753				-0.0094	0.0242	0.698
Design of the analysis									
Quadratic	-0.0487	0.0115	0.9977	-0.0260	0.0170	0.124	-0.0404	0.0194	0.038
Endogeneity	0.0005	0.0039	0.0513						
Macro	0.0010	0.0099	0.0582						
Averaged	0.0570	0.0247	0.9052	0.0380	0.0263	0.149			
Treatment of stability									
Dummies	-0.1562	0.0333	0.9990	-0.1759	0.0372	0.000	-0.1956	0.0401	0.000
NPL	0.0001	0.0019	0.0362						

Response variable	Bayesian model averaging			OLS			OLS (Z&H's variable selection criteria)		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Z_score	0.0000	0.0015	0.0361						
Profit volatility	0.0000	0.0042	0.0345						
Profitability	-0.0006	0.0042	0.0529						
Capitalization	-0.0001	0.0036	0.0350						
DtoD	-0.1008	0.0269	0.9909	-0.0789	0.0353	0.025			
Treatment of competition									
H-statistic	0.1021	0.0167	1.0000	0.1051	0.0278	0.000	0.0976	0.0327	0.003
Boone	-0.0008	0.0061	0.0675				-0.0011	0.0221	0.962
Concentration	-0.0012	0.0066	0.0694						
Lerner	0.0318	0.0124	0.9546	0.0054	0.0155	0.728			
HHI	0.0023	0.0079	0.1168						
Estimation method									
Logit	0.1605	0.0270	1.0000	0.1737	0.0348	0.000	0.1800	0.0445	0.000
OLS	0.0003	0.0038	0.0471				-0.0040	0.0247	0.871
FE	0.0005	0.0043	0.0462						
RE	0.0888	0.0237	0.9955	0.0854	0.0434	0.049			
GMM	0.0059	0.0127	0.2232						
TSLS	0.0004	0.0044	0.0432						

Response variable	Bayesian model averaging			OLS			OLS (Z&H's variable selection criteria)		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Control variables									
Regulation	-0.0105	0.0157	0.3696				0.0032	0.0143	0.825
Ownership	-0.0318	0.0180	0.8219	-0.0304	0.0226	0.179			
Global	0.0385	0.0107	0.9862	0.0217	0.0178	0.224			
Publication characteristics									
Citations	0.0726	0.0088	1.0000	0.0586	0.0163	0.000	0.0613	0.0233	0.009
Firstpub	0.0328	0.0041	1.0000	0.0260	0.0079	0.001	0.0231	0.0080	0.004
IFrecursive	0.0007	0.0073	0.0437				-0.0748	0.0548	0.172
Reviewed journal	-0.1172	0.0115	1.0000	-0.0789	0.0237	0.001	-0.0782	0.0310	0.012
Constant	-0.0012	NA	1.0000	-0.0292	0.1118	0.794	0.0216	0.1174	0.854
Studies			31			31			31
Observations			598			598			598

Note. The table presents results from data re-coding. OLS estimation includes explanatory variables with PIP greater than 0.5. OLS (Z&H's variable selection criteria) includes explanatory variables from Table 3.5.1. The standard errors are clustered at the study level. Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. The inverse number of estimates per study is taken as the weight.

Table 3.5.2 follows the same procedure as Table 3.5.1 except that it uses the re-coded data for the BMA analysis and OLS estimation. There are two OLS regressions in Table 3.5.2. The first OLS regression ("OLS") includes all variables having a PIP value greater than 0.50 in Table 3.5.2. The second OLS regression ("OLS - Z&H's variable selection criteria") uses the same variables that were included in Z&H's OLS regression of Table 3.5.1.

3.5.1 Comparison of BMA results from Tables 5.1 and 5.2

As noted previously, while generally similar, there are some differences in Z&H's data and the re-coded data. These differences, in turn, produce somewhat different BMA and OLS results in Tables 3.5.1 and 3.5.2. In Table 3.5.1, there are 15 variables with PIP values greater than 0.5. Table 3.5.2 reports 17 variables with PIP values greater than 0.5. The characteristics sample size, developing and transition countries, Boone, OLS estimation, controls for regulation, and the recursive impact factor are significantly associated with estimated competition effect sizes in Table 3.5.1 (5 percent level) but not Table 3.5.2 (cf. "OLS - Z&H's variable selection criteria"). Further, the variables mean value of the sample period (Sampleyear), estimation of competition and stability using country-level averages (Averaged), distance-to-default (DtoD), Lerner index, random effects estimation (RE), controls for bank ownership (Ownership), and controls for macroeconomic conditions (Global) all had PIP values greater than 0.5 using the re-coded data and were selected for OLS estimation in Table 3.5.2 (cf. "OLS" results), but were not selected for OLS estimation in Table 3.5.1. While some of the estimated mean effects in the BMA analysis switched signs between Tables 3.5.1 and 3.5.2, of these, only Dummies and Logit had PIP values larger than 0.5 in both tables.

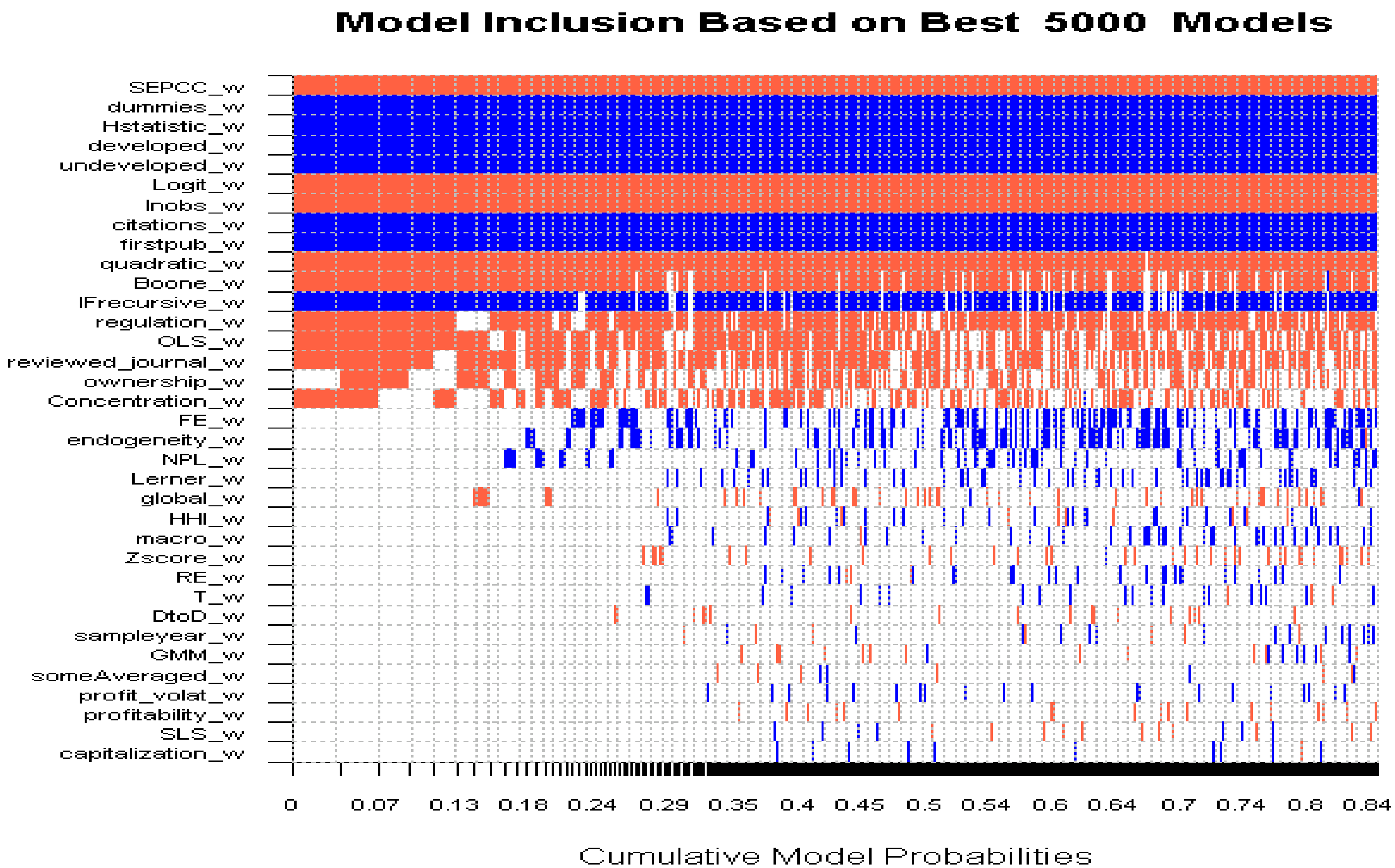


Figure 3.5A: Bayesian Model Averaging: Model Inclusion Probability

Note. The figure illustrates results of BMA exercise. This is produced from Zigraiova and Havranek (2016) dataset. Columns represent individual models and rows represent explanatory variables. Explanatory variables are sorted by their PIP in descending order. The positive coefficient sign denoted by blue color, negative coefficients in red color and the excluded variables from a model is left blank.

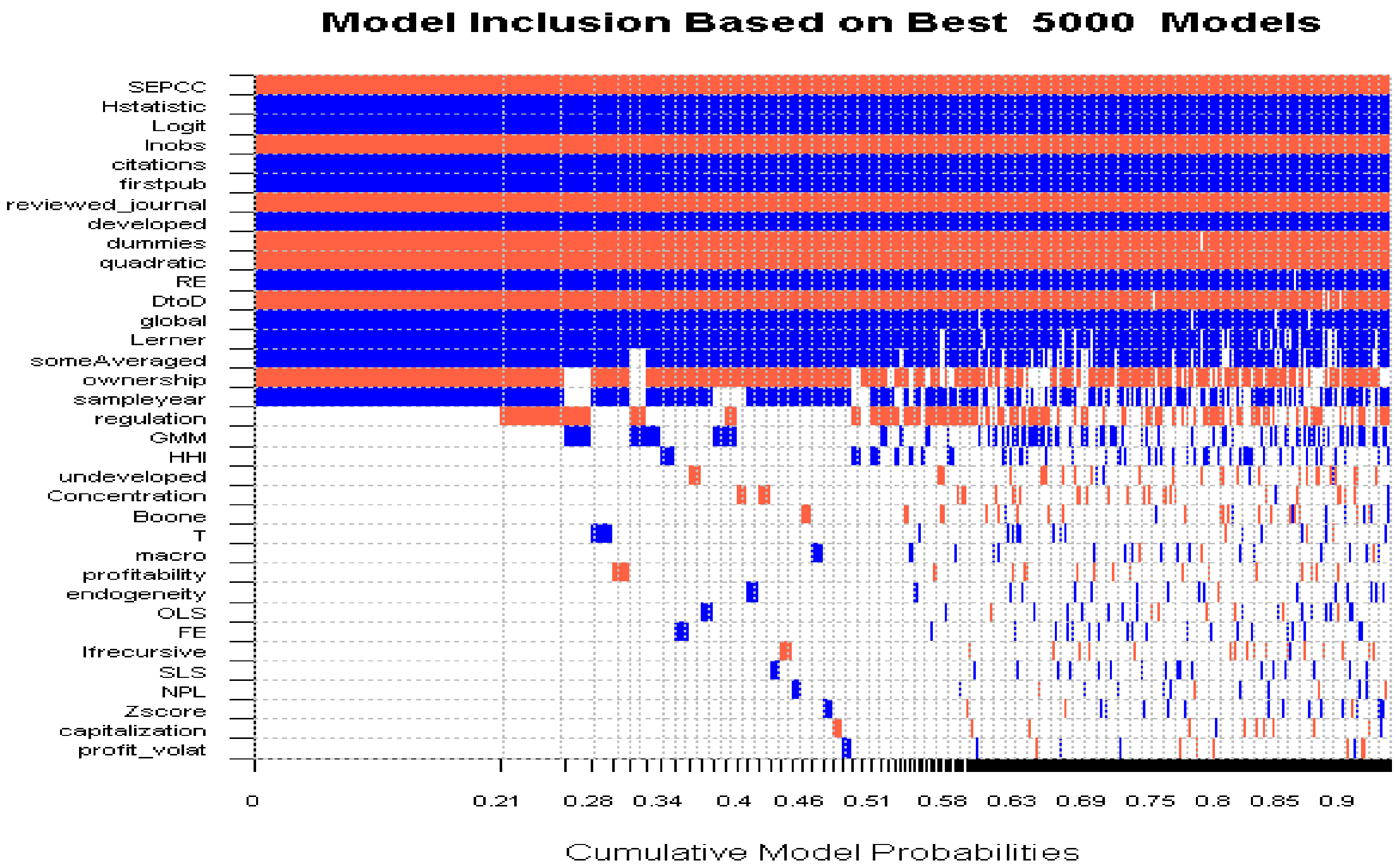


Figure 3.5B: Bayesian Model Averaging: Model Inclusion Probability

Note. The figure illustrates results of BMA exercise. This is produced from re-coded data from same studies considered by Zigraiova and Havranek (2016). Columns represent individual regression models and rows represent explanatory variables. Explanatory variables are sorted by their PIP in descending order. The positive coefficient sign denoted by blue color, negative coefficients in red color and the excluded variables from a model is left blank.

Figures 3.5A and 3.5B graphically illustrate the results of the BMA exercise. The top 5000 models are represented, with most likely models ordered from left to right, and most frequently included variables ordered from top to bottom. The 5000 models cumulatively account for an inclusion probability of 84 percent in Figure 3.5A, and 90 percent in Figure 3.5B. Colors indicate the sign of the estimated mean effects (blue = positive, red = negative). Uncolored cells indicate that a variable was not included in the respective model.

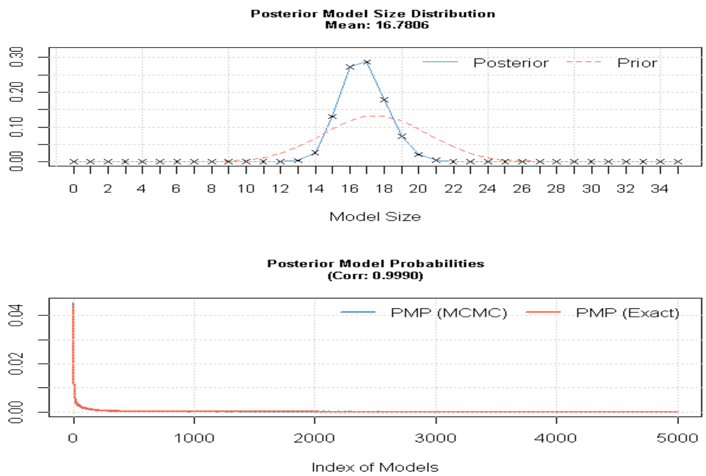


Figure 3.6A:
Model Size and Convergence from Zigraiova and Havranek (2016) Dataset

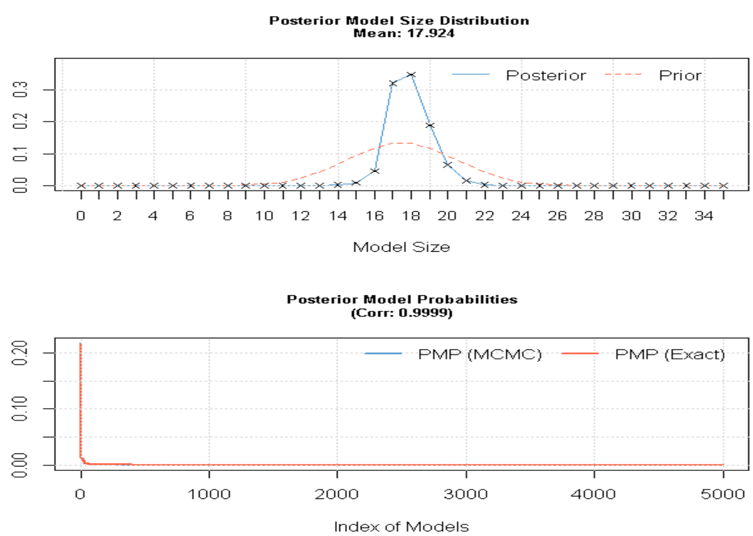


Figure 3.6B:
Model Size and Convergence from Re-coded Data

Figures 3.6A and 3.6B report various diagnostics associated with the BMA analysis. The top panels of the figures illustrate the posterior expected model size. It is 16.7806 in Figure 3.6A. This means that, on average, 17 regressors are included in a given estimation model. In Figure 3.6B, the posterior expected model indicates that 18 regressors are included, on average, in a given model. The bottom panels of the graphs illustrate the correlation between iteration counts and posterior model probability for the best 5000 models. The fact that the correlations are very close to one identify a high degree of convergence of the best 5000 models.

3.6 Best Practice Estimates

This section predicts the estimated effect of competition on financial stability from a hypothetical study that employs "best practice" in estimating the relationship between competition and stability. The explanatory variables used for the predictions are taken from the set of variables determined to be "important" in the BMA analysis of the previous section (i.e., having a PIP greater than 0.5). "Best practice" is determined by a subjective judgment of which variable values would be most preferred in an ideal study.

For the continuous variables chosen for this exercise -- sample size, the recursive impact factor, number of citations, studies published in peer reviewed journal, controls for regulatory environment, and the Boone index -- Z&H used the sample maxima, as they judged that studies with larger values for these variables are higher quality studies. . Z&H assigned zero to SEPCC, as the ideal study would not have publication bias. Zero values were also assigned to dummy variable as a measure of stability, OLS estimation, Logit estimation, quadratic relationship between competition and stability, and H-statistic, as these were deemed not best practice. Sample means were used for all the other variables.

Table 3.6 shows weighted and unweighted PCCs based on the best practice estimates. Results are given in three panels. Panel A presents best practice estimates using Z&H's dataset. The weighted explanatory variables are taken from Table 3.5.1 and the unweighted explanatory variables are taken from Table 3.8.1. Panel B selects variables from the re-coded data. Panel C also uses re-coded data, but the estimation is based on Z&H's variable selection. The weighted variables for panels B and C are taken from Table 3.5.2 and the unweighted variables are from Table 3.8.2.

Table 3.6 shows both weighted and unweighted, predicted values of PCCs, along with associated 95 percent confidence intervals. The columns named as "Diff." show the difference between the best practice estimates and the sample estimates in Table 3.1. Results are presented for three groups: all estimates, developed countries, and developing and transition countries. The "Diff." columns indicate that the best practice PCCs are generally larger than the PCC values of Table 3.1.

With respect to the weighted estimates, panel A reports "small" effect sizes for the samples of all observations and estimates derived from developing and transition countries, where "small" is defined as a PCC value less than 0.07. Both predicted PCC values are statistically insignificant. In contrast, the best practice PCC for developed countries is medium-sized and statistically significant. Unweighted estimation results are not too dissimilar from the weighted results, and are statistically significant for all three country categories.

Panel B reports small effects (< 0.07) in most of the cases. The best-practice estimates are statistically significant in developed countries for both weighted and unweighted estimations. Panel C also generally finds small effects sizes, with none of the predicted values being statistically significant at the 5 percent level. Overall, best-practice estimates find a positive, albeit small, relationship between bank competition and financial stability.

Table 3.6

Best-Practice Estimates of the Competition Coefficient

	Weighted				Unweighted			
	Mean	**95% CI**		**Diff.**	**Mean**	**95% CI**		**Diff.**
				Panel A				
All	0.022	−0.022	0.066	0.034	0.038**	0.000	0.076	0.039
Developed	0.096***	0.049	0.144	0.085	0.091***	0.045	0.137	0.071
Developing and transition	0.019	−0.035	0.072	0.038	0.055**	0.011	0.099	0.054
				Panel B				
All	0.039	-0.010	0.088	0.040	0.006	-0.027	0.039	-0.003
Developed	0.078**	0.014	0.143	0.058	0.045**	0.010	0.081	0.020
Developing and transition	0.037	-0.013	0.087	0.049	0.045**	0.007	0.084	0.039
				Panel C				
All	0.024	-0.040	0.089	0.025	0.023	-0.055	0.100	0.014
Developed	0.076*	-0.003	0.154	0.056	0.057	-0.024	0.137	0.032

	Weighted				Unweighted			
	Mean	**95% CI**		**Diff.**	**Mean**	**95% CI**		**Diff.**
Developing and transition	-0.001	-0.073	0.071	0.011	0.036	-0.053	0.124	0.030

Note. The table presents the mean PCCs of competition coefficient estimates for all competition coefficient estimates, those from developed (OECD) countries, and those from developing and transition (non-OECD) countries. The left side of the table reports weighted estimates by inverse number of estimates per study. The right side of the table presents unweighted mean PCCs of competition coefficient estimates. Panel A reports the mean PCCs by using Zigraiova and Havranek (2016) dataset. The explanatory variables are selected with PIP > 0.5, from Table 3.5.1 and Table 3.8.1. Panel B reports mean PCCs by using data re-coding and the variables with PIP > 0.5 are taken from Table 3.5.2 and Table 3.8.2. Panel C reports mean PCCs by using data re-coding and the variable selection is based on Z&H's variable selection criteria. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

3.7 Robustness Checks

Z&H presented four robustness checks in their study. This analysis follows suit and performs the same four checks. Section 3.7.1 reports a BMA exercise with alternative priors. Section 3.7.2 uses unweighted estimates with the baseline priors used in Tables 3.5.1 and 3.5.2. Section 3.7.3 reports results with OLS and fixed effects estimation methods. Finally, Section 3.7.4 uses an inverse of the estimate variance as the weighting method to weight explanatory variables.

3.7.1 Alternative BMA priors

In their main estimates, Z&H chose Zellner's g-prior for the unit information prior, and used the uniform model prior. As alternatives, Z&H selected the benchmark prior (BRIC) and the random model prior.

Tables 3.7.1 and 3.7.2 show the results based on BMA with the alternative priors. As before, the associated OLS regressions restrict variables to those having PIP values greater than 0.5. Table 3.7.1 reports results using Z&H's data. The results are very similar to the baseline BMA results of Table 3.5.1. Table 3.7.2 reports the results using the re-coded data, following the same procedures used for Table 3.5.2. The first OLS regression includes the 17 variables with PIP values more than 0.5 using the re-coded data. The second set of OLS results uses the 15 variables selected from the BMA analysis based on Z&H's data. The results of Table 3.7.2 are very similar to Table 3.5.2.

Table 3.7.1

Results with Alternative BMA Priors

Response variable	**Bayesian model averaging**			**OLS**		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-1.7526	0.2122	1.0000	-1.194	0.651	0.067
Samplesize	-0.0362	0.0036	1.0000	-0.024	0.009	0.007
T	-0.0003	0.0034	0.0373			
Sampleyear	-0.0000	0.0004	0.0336			
Countries examined						
Developed	0.1975	0.0248	1.0000	0.176	0.029	0.000
Developing and transition	0.1030	0.0188	1.0000	0.099	0.026	0.000
Design of the analysis						
Quadratic	-0.0517	0.0141	0.9882	-0.044	0.013	0.001
Endogeneity	0.0159	0.0270	0.3039			
Macro	0.0028	0.0132	0.0672			
Averaged	-0.0004	0.0043	0.0309			

Response variable	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Treatment of stability						
Dummies	0.2179	0.0315	1.0000	0.184	0.019	0.000
NPL	0.0012	0.0047	0.0818			
Z_score	-0.0004	0.0023	0.0426			
Profit volatility	-0.0004	0.0043	0.0255			
Profitability	-0.0002	0.0024	0.0236			
Capitalization	0.0000	0.0024	0.0185			
DtoD	-0.0007	0.0060	0.0313			
Treatment of competition						
H-statistic	0.1074	0.0228	1.0000	0.114	0.018	0.000
Boone	-0.0637	0.0375	0.8017	-0.058	0.023	0.010
Concentration	-0.0182	0.0244	0.4181			
Lerner	0.0032	0.0128	0.0946			
HHI	0.0021	0.0107	0.0659			
Estimation method						
Logit	-0.1883	0.0237	1.0000	-0.160	0.019	0.000
OLS	-0.0295	0.0265	0.6206	-0.038	0.018	0.038
FE	0.0160	0.0258	0.3263			
RE	0.0020	0.0120	0.0522			
GMM	-0.0002	0.0023	0.0272			
TSLS	-0.0018	0.0031	0.0257			
Control variables						
Regulation	-0.0313	0.0205	0.7623	-0.036	0.014	0.010
Ownership	-0.0129	0.0176	0.4015			
Global	-0.0013	0.0051	0.0838			
Publication characteristics						
Citations	0.0476	0.0101	0.9999	0.046	0.009	0.000
Firstpub	0.0207	0.0051	0.9999	0.023	0.003	0.000
IFrecursive	0.0958	0.0622	0.7698	0.096	0.048	0.000

Response variable	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Reviewed journal	-0.0211	0.0198	0.6026	-0.015	0.014	0.289
Constant	-0.0004	NA	1.0000	-0.118	0.086	0.169
Studies			31			31
Observations			598			598

Note. The table presents BMA results and OLS estimation from data published by Zigraiova and Havranek (2016). Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. OLS estimation includes explanatory variables with PIP greater than 0.5. The standard errors are clustered at the study level. The inverse number of estimates per study is taken as the weight.

Table 3.7.2

Results with Alternative BMA Priors

Response variable	Bayesian model averaging			OLS			OLS (Z&H's variable selection criteria)		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Data characteristics									
SEPCC	-1.8036	0.1952	1.0000	-1.4576	0.8458	0.085	-1.3625	0.9114	0.135
Samplesize	-0.0355	0.0060	1.0000	-0.0290	0.0143	0.042	-0.0258	0.0150	0.085
T	0.0004	0.0033	0.0454						
Sampleyear	0.0032	0.0025	0.6767	0.0033	0.0034	0.324			
Countries examined									
Developed	0.0505	0.0094	0.9985	0.0528	0.0212	0.013	0.0678	0.0292	0.020
Developing and transition	-0.0013	0.0066	0.0671				-0.0094	0.0242	0.698
Design of the analysis									
Quadratic	-0.0484	0.0118	0.9950	-0.0260	0.0170	0.124	-0.0404	0.0194	0.038
Endogeneity	0.0004	0.0037	0.0409						
Macro	-0.0007	0.0100	0.0474						
Averaged	0.0522	0.0283	0.8306	0.0380	0.0263	0.149			
Treatment of stability									
Dummies	-0.1596	0.0358	0.9978	-0.1759	0.0372	0.000	-0.1956	0.0401	0.000
NPL	0.0001	0.0016	0.0266						
Z score	-0.0000	0.0013	0.0271						

Response variable	Bayesian model averaging			OLS			OLS (Z&H's variable selection criteria)		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Profit volatility	-0.0000	0.0036	0.0253						
Profitability	-0.0005	0.0036	0.0390						
Capitalization	-0.0001	0.0031	0.0257						
DtoD	-0.0961	0.0323	0.9576	-0.0789	0.0353	0.025			
Treatment of competition									
H-statistic	0.1029	0.0169	1.0000	0.1051	0.0278	0.000	0.0976	0.0327	0.003
Boone	-0.0007	0.0057	0.0548				-0.0011	0.0221	0.962
Concentration	-0.0011	0.0064	0.0580						
Lerner	0.0305	0.0130	0.9311	0.0054	0.0155	0.728			
HHI	0.0018	0.0072	0.0928						
Estimation method									
Logit	0.1627	0.0285	1.0000	0.1737	0.0348	0.000	0.1800	0.0445	0.000
OLS	0.0002	0.0033	0.0355				-0.0040	0.0247	0.871
FE	0.0004	0.0037	0.0337						
RE	0.0904	0.0247	0.9932	0.0854	0.0434	0.049			
GMM	0.0081	0.0149	0.2670						
TSLS	0.0004	0.0045	0.0358						
Control variables									
Regulation	-0.0094	0.0153	0.3252				0.0032	0.0143	0.825

Response variable	Bayesian model averaging			OLS			OLS (Z&H's variable selection criteria)		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Ownership	-0.0303	0.0189	0.7799	-0.0304	0.0226	0.179			
Global	0.0364	0.0129	0.9491	0.0217	0.0178	0.224			
Publication characteristics									
Citations	0.0712	0.0096	1.0000	0.0586	0.0163	0.000	0.0613	0.0233	0.009
Firstpub	0.0322	0.0046	1.0000	0.0260	0.0079	0.001	0.0231	0.0080	0.004
IFrecursive	-0.0010	0.0085	0.0394				-0.0748	0.0548	0.172
Reviewed journal	-0.1162	0.0122	1.0000	-0.0789	0.0237	0.001	-0.0782	0.0310	0.012
Constant	-0.0012	NA	1.0000	-0.0292	0.1118	0.794	0.0216	0.1174	0.854
Studies			31			31			31
Observations			598			598			598

Note. The table presents results from data re-coding. OLS estimation includes explanatory variables with PIP greater than 0.5. OLS (Z&H's variable selection criteria) includes explanatory variables from Table 3.7.1. The standard errors are clustered at the study level. The inverse number of estimates per study is taken as the weight. Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability.

3.7.2 Unweighted regressions

Table 3.8.1 reports BMA results for unweighted regressions based on Z&H's dataset. There are 14 variables with PIP values greater than 0.5. These are subsequently included in the OLS estimation. Interestingly, the PIP value for the publication bias variable (SEPCC) is relatively low compared to previous BMA analyses, but it is still greater than 0.50. As the unweighted regressions produce somewhat different BMA/PIP values compared to the weighted regressions, different variable selections ensue.

The following variables have PIP values equal to, or close to, 1.0000: sample size, developed countries, developing and transition countries, crisis as a dummy variable, profitability, H-statistic, Logit estimation, fixed effects estimation, two-stage least squares estimation (TSLS), controls for bank ownership, number of citations, the year when the study first appeared in Google Scholar, and the journal impact factor. Studies with a large sample size are associated with slightly lower effect size estimates. Studies of banking competition and financial stability using data from developed or developing and transition countries are associated with substantially higher effect sizes than studies that have a mix of countries. Studies that use a dummy variable as a measure of financial stability also tend to have larger effect sizes. Studies that measure stability by "profitability" have slightly lower estimates, while the use of H-statistic to measure competition is associated with larger estimates. The BMA analysis suggests that studies that employ logit analysis tend to have lower effect sizes, while those that use panel fixed effects or correct for endogeneity (TSLS) tend to have somewhat higher estimates. Boyd et al. (2006); De Nicolo and Loukoianova (2007) recommend that studies include a variable for bank ownership controls in the competition-stability equation, and the BMA results provide moderate support for this. Lastly, higher quality studies, as measured by citations, early publication date, and journal impact factor, tend to increase the competition coefficient.

Table 3.8.1

Results for Unweighted Regressions

Response variable	**Bayesian model averaging**				**OLS**	
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-0.7259	0.5667	0.7003	-0.5768	0.7862	0.463
Samplesize	-0.0258	0.0082	1.0000	-0.0248	0.0092	0.007
T	0.0008	0.0034	0.0735			
Sampleyear	0.0006	0.0015	0.1946			
Countries examined						
Developed	0.1530	0.0172	1.0000	0.1519	0.0175	0.000
Developing and transition	0.1267	0.0172	1.0000	0.1156	0.0170	0.000
Design of the analysis						
Quadratic	0.0012	0.0050	0.0755			
Endogeneity	0.0056	0.0110	0.2461			
Macro	-0.0102	0.0161	0.3408			
Averaged	-0.0000	0.0024	0.0219			
Treatment of stability						
Dummies	0.1861	0.0281	1.0000	0.1660	0.0176	0.000
NPL	0.0138	0.0249	0.2739			
Z_score	0.0091	0.0167	0.2660			
Profit volatility	0.0176	0.0238	0.4350			
Profitability	-0.0281	0.0232	0.6587	-0.0451	0.0246	0.066
Capitalization	0.0101	0.0196	0.2437			
DtoD	-0.0015	0.0080	0.0674			
Treatment of competition						
H-statistic	0.1294	0.0223	1.0000	0.1123	0.0173	0.000

Response variable	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Boone	-0.0021	0.0088	0.0873			
Concentration	0.0159	0.0244	0.3626			
Lerner	0.0136	0.0211	0.3566			
HHI	0.0103	0.0199	0.2488			
Estimation method						
Logit	-0.1304	0.0303	0.9999	-0.1275	0.0121	0.000
OLS	0.0000	0.0019	0.0214			
FE	0.0621	0.0134	1.0000	0.0503	0.0113	0.000
RE	0.0128	0.0204	0.3355			
GMM	0.0000	0.0018	0.0221			
TSLS	0.0532	0.0132	0.9999	0.0515	0.0147	0.000
Control variables						
Regulation	0.0002	0.0020	0.0281			
Ownership	-0.0595	0.0096	1.0000	-0.0588	0.0289	0.042
Global	0.0016	0.0054	0.1033			
Publication characteristics						
Citations	0.0377	0.0063	0.9996	0.0407	0.0087	0.000
Firstpub	0.0179	0.0033	0.9997	0.0205	0.0029	0.000
IFrecursive	0.0470	0.0419	0.6405	0.0490	0.0379	0.196
Reviewed journal	0.0019	0.0080	0.0807			
Constant	-0.1269	NA	1.0000	-0.1263	0.0870	0.146
Studies			31			31
Observations			598			598

Note. The table presents BMA results and OLS estimation from data published by Zigraiova and Havranek (2016). Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. OLS estimation includes explanatory variables with PIP greater than 0.5. The standard errors are clustered at the study level.

Table 3.8.2

Results for Unweighted Regressions

Response variable	Bayesian model averaging			OLS			OLS (Z&H variable selection)		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Data characteristics									
SEPCC	-1.9396	0.4485	0.9949	-1.9260	1.1943	0.107	0.2945	1.5383	0.848
Samplesize	-0.0231	0.0065	0.9879	-0.0228	0.0125	0.069	-0.0075	0.0169	0.656
T	0.0000	0.0015	0.0464						
Sampleyear	0.0078	0.0015	1.0000	0.0092	0.0034	0.006			
Countries examined									
Developed	0.0912	0.0145	1.0000	0.0802	0.0127	0.000	0.0578	0.0243	0.017
Developing and transition	0.0940	0.0151	1.0000	0.0805	0.0226	0.000	0.0370	0.0220	0.093
Design of the analysis									
Quadratic	0.0018	0.0063	0.1102						
Endogeneity	0.0587	0.0103	1.0000	0.0634	0.0133	0.000			
Macro	0.2082	0.0295	1.0000	0.1935	0.0588	0.001			
Averaged	0.1059	0.0275	0.9969	0.0884	0.0420	0.035			
Treatment of stability									
Dummies	-0.2766	0.0337	1.0000	-0.2498	0.0251	0.000	-0.2333	0.0375	0.000
NPL	0.0023	0.0089	0.0973						
Z_score	0.0004	0.0038	0.0525						

Response variable	Bayesian model averaging			OLS			OLS (Z&H variable selection)		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Profit volatility	0.0017	0.0067	0.0939						
Profitability	-0.0394	0.0206	0.8639	-0.0477	0.0244	0.050	-0.0378	0.0210	0.072
Capitalization	0.0007	0.0048	0.0538						
DtoD	-0.0003	0.0045	0.0477						
Treatment of competition									
H-statistic	0.0994	0.0132	1.0000	0.1001	0.0275	0.000	0.0785	0.0378	0.038
Boone	0.0003	0.0037	0.0428						
Concentration	0.0012	0.0063	0.0690						
Lerner	0.0139	0.0167	0.4764						
HHI	0.0002	0.0039	0.0483						
Estimation method									
Logit	0.2462	0.0296	1.0000	0.2229	0.0145	0.000	0.2118	0.0389	0.000
OLS	0.0742	0.0137	1.0000	0.0697	0.0151	0.000			
FE	0.0900	0.0151	1.0000	0.0863	0.0181	0.000	0.0124	0.0217	0.566
RE	0.1025	0.0178	1.0000	0.1026	0.0457	0.025			
GMM	0.0019	0.0078	0.0880						
TSLS	0.0853	0.0136	1.0000	0.0868	0.0139	0.000	0.0074	0.0260	0.776
Control variables									
Regulation	0.0004	0.0027	0.0532						

Response variable	Bayesian model averaging			OLS			OLS (Z&H variable selection)		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Ownership	-0.0368	0.0099	0.9927	-0.0331	0.0259	0.202	-0.0342	0.0305	0.263
Global	0.0002	0.0027	0.0422						
Publication characteristics									
Citations	0.0096	0.0091	0.6251	0.0100	0.0076	0.186	0.0298	0.0179	0.096
Firstpub	0.0024	0.0036	0.3731				0.0118	0.0064	0.063
IFrecursive	-0.0006	0.0062	0.0441				-0.0105	0.0552	0.849
Reviewed journal	0.0000	0.0048	0.0799						
Constant	-0.0471	NA	1.0000	-0.0342	0.1030	0.740	-0.1044	0.1374	0.447
Studies			31			31			31
Observations			598			598			598

Note. The table presents results from data re-coding. OLS estimation includes explanatory variables with PIP greater than 0.5. OLS (Z&H's variable selection criteria) includes explanatory variables from Table 3.8.1. The standard errors are clustered at the study level. Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability.

Table 3.8.2 reports BMA and OLS results for unweighted regressions using the re-coded data. There are 18 variables with PIPs greater than 0.5. The OLS regression results are similar to the BMA results. The last three columns show OLS estimates from variable selection based on BMA analysis of Z&H's data (cf. Table 3.8.1). Tables 3.8.1 and 3.8.2 again confirm the presence of publication bias in the literature.

3.7.3 Frequentist methods (all variables)

Table 3.9.1 reports an analysis based on OLS and fixed effects estimation methods in which all possible variables are included in the estimation. Table 3.9.1 uses the authors' data. The left side of the table reports OLS results, and the right side of the table shows the results from panel fixed effects estimation. Note that some of the variables take on the same value for all estimates from the same study and thus cannot be included in fixed effects estimation. For example, measures of publication quality such as citations, first date of publication, and impact factor will be identical for every estimate from the same study.

SEPCC is significant at the 10 percent level in the OLS regression, and the 5 percent level in the panel fixed effects regression. Both estimation methods confirm the presence of negative publication bias. Based on OLS estimation, the following variables are statistically significant at the 5 percent level: sample size; OECD and non-OECD countries relative to estimates from studies with mixed countries; dummies as a measure of stability, H-statistic and Lerner index as measures of competition; logit and fixed effects among estimation methods; and citations, year of first publication and impact factor as measures of publication quality.

Fixed effects estimation omits all the variables constant within studies. The results indicate that among data charactersitics, SEPCC is the statistically significant variable at the 5 percent level. Among variables characterizing analysis design, Macro is significant. None of the variables providing different ways of measuring stability is significant (the reference group is all other ways of measuring stability), while all the variables measuring competition are significant (reference group is all other ways of measuring competition). Among estimation procedures, OLS, FE, and GMM are significant.

Table 3.9.1

Results for Frequentist Methods

Response variable		**OLS**			**Fixed effects**	
Competition effect	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-1.5708	0.8567	0.067	-1.6234	0.6912	0.026
Samplesize	-0.0363	0.0110	0.001	0.0148	0.0212	0.491
T	0.0141	0.0107	0.188	-0.0511	0.0268	0.067
Sampleyear	0.0040	0.0033	0.222	0.0057	0.0032	0.082
Countries examined						
Developed	0.1689	0.0211	0.000	-0.1020	0.0760	0.189
Developing and transition	0.1008	0.0166	0.000	Omitted		
Design of the analysis						
Quadratic	-0.0080	0.0204	0.694	-0.0071	0.0135	0.604
Endogeneity	0.0240	0.0292	0.410	-0.0292	0.0163	0.084
Macro	-0.0040	0.0364	0.914	0.1882	0.0138	0.000
Averaged	-0.0023	0.0285	0.935	0.0226	0.0151	0.146
Treatment of stability						
Dummies	0.2232	0.0373	0.000	Omitted		
NPL	0.0299	0.0259	0.250	0.0239	0.0232	0.310
Z_score	0.0116	0.0249	0.641	0.0172	0.0228	0.456
Profit volatility	0.0284	0.0206	0.168	0.0192	0.0214	0.378
Profitability	-0.0142	0.0269	0.600	-0.0048	0.0270	0.860
Capitalization	0.0184	0.0240	0.443	0.0052	0.0254	0.838
DtoD	-0.0157	0.0337	0.641	0.0217	0.0284	0.452

Response variable	OLS			Fixed effects		
Competition effect	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Treatment of competition						
H-statistic	0.1629	0.0308	0.000	0.0577	0.0201	0.007
Boone	0.0010	0.2071	0.970	0.0744	0.0112	0.000
Concentration	0.0351	0.0356	0.324	0.0709	0.0346	0.050
Lerner	0.0485	0.0188	0.010	0.0721	0.0189	0.001
HHI	0.0444	0.0257	0.084	0.0654	0.0252	0.014
Estimation method						
Logit	-0.1481	0.0405	0.000	Omitted		
OLS	-0.0022	0.0218	0.919	0.0225	0.0108	0.045
FE	0.0624	0.0247	0.011	0.0392	0.0180	0.038
RE	0.0317	0.0382	0.406	-0.0042	0.0182	0.819
GMM	0.0014	0.0159	0.932	0.0437	0.0206	0.043
TSLS	0.0393	0.0230	0.087	0.0223	0.0186	0.239
Control variables						
Regulation	-0.0184	0.0138	0.181	0.0062	0.0104	0.558
Ownership	-0.0341	0.0227	0.133	-0.0193	0.0311	0.539
Global	0.0112	0.0176	0.524	0.2391	0.0152	0.125
Publication characteristics						
Citations	0.0408	0.0146	0.005	Omitted		
Firstpub	0.0159	0.0067	0.017	Omitted		
IFrecursive	0.0890	0.0363	0.014	Omitted		
Reviewed journal	-0.0042	0.0271	0.876	Omitted		
Constant	-0.1350	0.1124	0.230	-0.1026	0.1570	0.518
Studies			31			31
Observations			598			598

Note. The table presents OLS and fixed effects estimations from data published by Zigraiova and Havranek (2016). The OLS and fixed effects include all the explanatory variables in the equation. The inverse number of estimates per study is taken as the weight. The standard errors are clustered at the study level.

Table 3.9.2 repeats the analysis with the re-coded data. While the publication bias variable SEPCC is significant in the OLS regression, it is insignificant in the panel fixed effects regression.

In summary, the results from the frequentist regressions are generally consistent with the baseline results in Section 3.5. In most cases, SEPCC is statistically significant and confirms the presence of publication bias.

Table 3.9.2

Results for Frequentist Methods

Response variable:		**OLS**			**Fixed effects**	
Competition effect	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-2.2989	0.7812	0.003	-5.0724	3.4733	0.155
Samplesize	-0.0429	0.0138	0.002	-0.0124	0.0279	0.660
T	0.0188	0.0138	0.174	-0.0613	0.0332	0.074
Sampleyear	0.0083	0.0036	0.023	0.0041	0.0009	0.000
Countries examined						
Developed	0.0706	0.0276	0.011	0.0123	0.0133	0.361
Developing and transition	0.0484	0.0269	0.072	0.1336	0.0897	0.147
Design of the analysis						
Quadratic	-0.0077	0.0175	0.659	-0.0090	0.0102	0.385
Endogeneity	0.0453	0.0167	0.007	0.0100	0.0147	0.502
Macro	0.1039	0.0463	0.025	0.3090	0.3192	0.341
Averaged	0.0988	0.0317	0.002	-0.0669	0.0093	0.000
Treatment of stability						
Dummies	-0.2185	0.0331	0.000	Omitted		
NPL	0.0213	0.0278	0.443	0.0274	0.0254	0.288

Response variable:	OLS			Fixed effects		
Competition effect	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Z_score	0.0158	0.0261	0.545	0.0145	0.0257	0.576
Profit volatility	0.0128	0.0207	0.537	0.0167	0.0231	0.474
Profitability	-0.0084	0.0270	0.755	0.0000	0.0270	0.999
Capitalization	0.0097	0.0245	0.693	0.0096	0.0269	0.723
DtoD	-0.0287	0.0398	0.471	0.0404	0.0300	0.188
Treatment of competition						
H-statistic	0.1480	0.0349	0.000	0.0707	0.0218	0.003
Boone	0.0429	0.0279	0.124	0.0828	0.0099	0.000
Concentration	0.0414	0.0354	0.242	0.1011	0.0286	0.001
Lerner	0.0543	0.0210	0.010	0.0793	0.0199	0.000
HHI	0.0266	0.0234	0.255	0.0656	0.0251	0.014
Estimation method						
Logit	0.2493	0.0501	0.000	Omitted		
OLS	0.0727	0.0269	0.007	0.0404	0.0113	0.001
FE	0.0883	0.0354	0.012	0.0467	0.0165	0.008
RE	0.1223	0.0440	0.005	0.0312	0.0178	0.090
GMM	0.0321	0.0295	0.278	0.0385	0.0192	0.054
TSLS	0.0735	0.0315	0.019	0.0312	0.0209	0.146
Control variables						
Regulation	-0.0069	0.0098	0.478	0.0178	0.0113	0.128
Ownership	-0.0222	0.020	0.268	-0.0066	0.0168	0.697
Global	0.0075	0.0153	0.625	0.0088	0.0139	0.534
Publication characteristics						
Citations	0.0535	0.0195	0.006	Omitted		
Firstpub	0.0171	0.0071	0.016	Omitted		
IFrecursive	-0.0286	0.0584	0.624	Omitted		

Response variable:	OLS			Fixed effects		
Competition effect	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Reviewed journal	-0.0681	0.0298	0.022	Omitted		
Constant	-0.0809	0.1132	0.475	0.1260	0.2934	0.671
Studies			31			31
Observations			598			598

Note. The OLS and fixed effects estimations include all the explanatory variables in the equation. The inverse number of estimates per study is taken as the weight. The standard errors are clustered at the study level.

3.7.4 Specifications weighted by inverse variance of the estimates

Section 3.7.4 uses a different weighting mechanism to weight the explanatory variables. Previous weighted estimates were based on the number of estimates per study. In this section, the estimation method weights by the inverse of the variance of the estimates. Table 3.10.1 reports results using Z&H's dataset. The BMA results are slightly different compared to the results in Z&H. However, the results from the OLS estimation are identical to their reported results. The high PIP of SEPCC again indicates negative publication. OLS also finds negative publication bias, but the associated coefficient is not significant. Overall, Table 3.10.1 supports the results of the earlier baseline results.

Table 3.10.1

Results for Specifications Weighted by Inverse Variance of the Estimates

Response variable	**Bayesian model averaging**				**OLS**	
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff.**	**SE**	**p-value**
Data characteristics						
SEPCC	-1.4214	NA	1.0000	-1.0152	0.9359	0.278
Samplesize	-0.0279	0.0039	1.0000	-0.0276	0.0067	0.000
T	0.0030	0.0054	0.2974	0.0177	0.0097	0.069
Sampleyear	0.0001	0.0007	0.0761	0.0043	0.0034	0.201
Countries examined						
Developed	0.1266	0.0074	1.0000	0.1257	0.0158	0.000
Developing and transition	0.0730	0.0065	1.0000	0.0729	0.0216	0.001
Design of the analysis						
Quadratic	0.0006	0.0028	0.0760	0.0059	0.0120	0.620
Endogeneity	0.0004	0.0032	0.0871	0.0060	0.0187	0.747
Macro	-0.0032	0.0069	0.2491	-0.0123	0.0190	0.519
Averaged	0.0003	0.0022	0.0562	0.0010	0.0125	0.934
Treatment of stability						
Dummies	0.2131	0.0268	1.0000	0.2346	0.0240	0.000
NPL	0.0442	0.0095	0.9999	0.0427	0.0231	0.065
Z_score	0.0384	0.0065	1.0000	0.0377	0.0192	0.049
Profit volatility	0.0581	0.0075	1.0000	0.0576	0.0187	0.002
Profitability	0.0135	0.0122	0.6226	0.0193	0.0153	0.207
Capitalization	0.0408	0.0075	1.0000	0.0402	0.0228	0.078
DtoD	0.0703	0.0105	1.0000	0.0776	0.0303	0.010
Treatment of competition						
H-statistic	0.0795	0.0133	1.0000	0.0866	0.0309	0.005
Boone	0.0000	0.0018	0.0358	0.0153	0.0155	0.323
Concentration	-0.0002	0.0029	0.0391	0.0084	0.0220	0.701
Lerner	-0.0000	0.0010	0.0354	0.0058	0.0055	0.297
HHI	0.0000	0.0012	0.0386	0.0108	0.0091	0.234

Response variable	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff.**	**SE**	**p-value**
Estimation method						
Logit	-0.1248	0.0273	0.9998	-0.1366	0.0352	0.000
OLS	-0.0002	0.0018	0.0428	0.0111	0.0227	0.626
FE	0.0697	0.0076	1.0000	0.0757	0.0207	0.000
RE	-0.0007	0.0068	0.0412	-0.0235	0.0619	0.704
GMM	0.0002	0.0016	0.0413	-0.0004	0.0197	0.980
TSLS	0.0504	0.0062	1.0000	0.0559	0.0218	0.010
Control variables						
Regulation	0.0002	0.0013	0.0637	0.0049	0.0059	0.409
Ownership	-0.0026	0.0066	0.1797	-0.0255	0.0210	0.226
Global	0.0004	0.0019	0.0776	0.0083	0.0143	0.561
Publication characteristics						
Citations	0.0227	0.0074	0.9405	0.0282	0.0131	0.032
Firstpub	0.0095	0.0031	0.9368	0.0050	0.0058	0.389
IFrecursive	-0.0006	0.0045	0.0472	-0.0131	0.0446	0.768
Reviewed journal	0.0027	0.0083	0.1374	0.0108	0.0213	0.612
Constant	-0.0004	0.0106	0.0414	-0.0845	0.0856	0.324
Studies			31			31
Observations			598			598

Note. The table presents BMA results and OLS estimation from data published by Zigraiova and Havranek (2016). Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. OLS estimation includes explanatory variables with PIP greater than 0.5. The standard errors are clustered at the study level.

Table 3.10.2 reports results using the re-coded data. The results generally align with previous findings. Among other things, the BMA and OLS analyses find moderate support for the existence of negative publication bias. The PIP value for SEPCC equals 1.000 in the BMA analysis, and the associated coefficient estimate is negative and significant at the 10 percent level in the OLS regression.

Table 3.10.2

Results for Specifications Weighted by Inverse Variance of the Estimates

Response variable	**Bayesian model averaging**			**OLS**		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-2.0504	NA	1.0000	-2.6040	1.3778	0.059
Samplesize	-0.0183	0.0029	0.9998	-0.0229	0.0086	0.008
T	-0.0006	0.0024	0.0872	0.0038	0.0092	0.677
Sampleyear	0.0005	0.0014	0.1609	0.0044	0.0028	0.118
Countries examined						
Developed	0.0801	0.0109	1.0000	0.0635	0.0203	0.002
Developing and transition	0.0773	0.0113	1.0000	0.0681	0.0274	0.013
Quadratic	-0.0001	0.0017	0.0372	-0.0011	0.0133	0.933
Design of the analysis						
Endogeneity	0.0039	0.0072	0.2847	0.0170	0.0082	0.038
Macro	0.1038	0.0262	0.9994	0.1256	0.0617	0.042
Averaged	0.0903	0.0156	1.0000	0.0646	0.0358	0.071
Treatment of stability						
Dummies	-0.2622	0.0294	1.0000	-0.2560	0.0326	0.000
NPL	0.0471	0.0097	0.9999	0.0447	0.0187	0.017
Z_score	0.0413	0.0062	1.0000	0.0409	0.0154	0.008
Profit volatility	0.0606	0.0074	1.0000	0.0589	0.0156	0.000
Profitability	0.0251	0.0111	0.9136	0.0252	0.0122	0.038
Capitalization	0.0462	0.0074	1.0000	0.0457	0.0171	0.008
DtoD	0.0764	0.0131	1.0000	0.0862	0.0203	0.000
Treatment of competition						
H-statistic	0.0387	0.0188	0.8899	0.0596	0.0232	0.010
Boone	0.0079	0.0133	0.3198	0.0407	0.0175	0.020
Concentration	-0.0007	0.0043	0.0578	-0.0027	0.0211	0.898
Lerner	-0.0001	0.0014	0.0409	0.0036	0.0103	0.728
HHI	-0.0002	0.0016	0.0439	0.0061	0.0094	0.518

Response variable	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Estimation method						
Logit	0.3012	0.0304	1.0000	0.3180	0.0361	0.000
OLS	0.0490	0.0145	0.9894	0.0760	0.0224	0.001
FE	0.0526	0.0148	0.9901	0.0798	0.0270	0.003
RE	0.0789	0.0172	0.9984	0.1087	0.0351	0.002
GMM	0.0047	0.0130	0.1972	0.0267	0.0240	0.264
TSLS	0.0426	0.0143	0.9852	0.0634	0.0276	0.022
Control variables						
Regulation	0.0010	0.0027	0.1440	0.0050	0.0051	0.332
Ownership	0.0002	0.0017	0.0448	-0.0041	0.0147	0.779
Global	0.0027	0.0050	0.2837	0.0078	0.0120	0.514
Publicationcharacteristics						
Citations	0.0025	0.0055	0.2284	0.0149	0.0155	0.337
Firstpub	0.0073	0.0027	0.9271	0.0043	0.0056	0.444
IFrecursive	-0.0238	0.0317	0.4360	-0.0728	0.0526	0.166
Reviewed journal	0.0017	0.0059	0.1234	0.0078	0.0237	0.741
Constant	0.0018	0.0143	0.0486	-0.0303	0.0963	0.753
Studies			31			31
Observations			598			598

Note. The table presents BMA results and OLS estimation from data re-coding. Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. OLS estimation includes explanatory variables with PIP greater than 0.5. The standard errors are clustered at the study level.

3.8 Corrections to the Dataset

When there is an interaction between an explanatory variable and another control variable, the competition effect depends not just on the estimated coefficient of the competition variable, but also on the value of the interacted control variable. Without further information about the control variable (say its sample mean), the interaction coefficients should not be included in the MRA. However, Z&H's dataset includes 52 competition measures where the competition variable interacts with another control variable. This section re-estimates the relationship between competition and stability by excluding these estimated effect sizes, reducing the total number of estimates to 546. Of these, 148 estimates are associated with developed countries, 152 with developing and transition countries, with the remaining 246 estimates belonging to the mixed country category.

Table 3.11

Estimate of the Competition Effect for Different Country Groups

Country group	**Unweighted**			**Weighted**			**No of estimates**
	Mean	**95% CI**		**Mean**	**95% CI**		
All	0.013	-0.013	0.039	0.002	-0.021	0.025	546
Developed	0.025***	0.007	0.043	0.019**	0.001	0.037	148
Developing and transition	0.008	-0.021	0.037	-0.004	-0.041	0.034	152

Note. The table presents the mean PCC of competition coefficient estimates for all estimates, estimates from developed (OECD) countries, and developing and transition (non-OECD) countries. The left side of the table presents, unweighted mean values and 95% confidence interval. In the right side of the table, estimates are weighted by inverse number of estimates per study. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 3.11 reports mean PCCs and their associated confidence intervals for weighted and unweighted estimates and the three country groups after correcting the dataset. The estimates find that the estimated competition effect is small (< 0.07). It is statistically insignificant for two of the country groupings (including the pooled sample of all estimates), while achieving statistical significance in the Developed country sample. These results are consistent with previously reported findings.

Table 3.12 reports the results of the FAT using the same dataset as Table 3.11. The null hypothesis of no publication bias is rejected at the 5 percent significance level in all specifications. The findings are consistent across estimation method (unweighted versus weighted, FE and instrumental variable methods) and across all studies and just published studies.

Table 3.12

Funnel Asymmetry Tests

Unweighted Regressions	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
SE (Publication bias)	-1.822**	-1.944**	-1.633***	-2.352***
Constant (effect beyond bias)	0.063***	0.082***	0.058***	0.096***
No of estimates	546	332	546	332
No of studies	31	21	31	21
Weighted Regressions	**FE**	**FE_Published**		
SE (Publication bias)	-1.615***	-1.607***		
Constant (effect beyond bias)	0.048***	0.044***		
No of estimates	546	332		
No of studies	31	21		

Note. The table presents the results of FAT. Top panel presents unweighted regressions and the bottom panel presents weighted regressions. The standard errors are clustered at the study level. Fixed effects estimation uses study dummies and instrumental variable estimation uses logarithm of the number of observations as the instrumental variable. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 3.13 shows heteroscedasticity-corrected FAT results. The regression estimates weighted by precision indicate that the results of 1/SE (effect beyond bias) are statistically significant at 5 percent level using instrumental variable estimation. The bottom panel of

Table 3.13 shows regression estimates weighted by precision and number of observations. The results are not statistically significant at 5 percent level. Further, all the estimates show a small (< 0.07) effect size. Overall, results are consistent with baseline specification and confirm publication bias in the literature.

Table 3.13

Heteroscedasticity-Corrected Funnel Asymmetry Tests

Weighted by precision	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
1/SE (effect beyond bias)	0.005	0.068	0.018**	0.056***
Constant (Publication bias)	-0.039	-3.192	-0.889	-2.560*
No of estimates	546	332	546	332
No of studies	31	21	31	18
Weighted by precision and No. of observations	**FE**	**FE_Published**		
1/SE (effect beyond bias)	0.014	0.049*		
Constant (Publication bias)	-1.123	-3.803**		
No of estimates	546	332		
No of studies	31	21		

Note. The table presents the results of Heteroscedasticity-corrected FAT. Top panel presents weighted regressions by precision and the bottom panel presents weighted regressions by precision and number of observations. The standard errors are clustered at the study level. Fixed effects estimation uses study dummies and instrumental variable estimation uses logarithm of the number of observations as the instrumental variable. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

3.9 Re-estimate the Results for Linear Coefficients

In total, 12 percent of the estimates use a quadratic specification to estimate the relationship between competition and financial stability. While Z&H combine the two relevant coefficients to obtain a single estimate of effect size (see their equation 6), they are unable to include the respective covariance term in calculating SEPCC due to the unavailability of data. This section investigates whether removing the associated effect estimates affects the results.

The analysis of this section removes the 70 quadratic estimates from the (corrected) sample of 546 estimates (cf. previous section), leaving a total sample size of 476 estimates based on linear specifications. 120 of these come from studies of developed countries, and another 143 come from studies of developing and transition countries. Table 3.14 reports estimates of the mean PCCs for the three country groupings. All the estimates are small in size, in line with previous estimates. Also consistent with previous results, the mean PCC values are only significant for developed countries.

Table 3.14

Estimate of the Competition Effect for Different Country Groups

Country Group	**Unweighted**			**Weighted**			**No of estimates**
	Mean	**95% CI**		**Mean**	**95% CI**		
All	0.016	-0.013	0.045	0.005	-0.024	0.034	476
Developed	0.033***	0.009	0.056	0.036***	0.015	0.056	120
Developing and transition	0.010	-0.021	0.040	0.001	-0.049	0.051	143

Note. The table presents the mean PCC of competition coefficient estimates for all estimates, estimates from developed (OECD) countries, and developing and transition (non-OECD) countries. The left side of the table presents, unweighted mean values and 95% confidence interval. In the right side of the table, estimates are weighted by inverse number of estimates per study. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 3.15

Funnel Asymmetry Tests

Unweighted Regressions	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
SE (Publication bias)	-1.847**	-1.979**	-1.666***	-2.502***
Constant (effect beyond bias)	0.067***	0.093***	0.062***	0.112***
No of estimates	476	279	476	279
No of studies	25	17	25	17
Weighted Regressions	**FE**	**FE_Published**		
SE (Publication bias)	-1.628***	-1.620***		
Constant (effect beyond bias)	0.051***	0.052***		
No of estimates	476	276		
No of studies	25	17		

Note. The table presents the results of the FAT. Top panel presents unweighted regressions and the bottom panel presents weighted regressions. The standard errors are clustered at the study level. Fixed effects estimation uses study dummies and instrumental variable estimation uses logarithm of the number of observations as the instrumental variable. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 3.15 reports the corresponding FAT results. The results indicate statistically significant publication bias in every regression. As expected, controlling for the negative publication bias causes the estimated effect size to increase (cf. “Constant – effect beyond bias”). However, even after controlling for publication bias, the estimated effect sizes continue to be relatively small, with most estimates remaining less than 0.07. The largest, publication-bias corrected estimate of the effect of competition on financial stability (as measured by the associated PCC) is 0.112 (cf. “Instrument Published”). The average value across the six estimates in the table is 0.073.

Finally, Table 3.16 reports heteroscedasticity-corrected FAT results using the sample of linear estimates. The analysis uncovers severe publication bias in published studies, but four of the six estimates are insignificant. Further, the bias-corrected effect sizes are now generally smaller. With one exception, they constitute “small” effects, where “small” is defined to be a PCC value less than 0.07 (Doucouliagos, 2011).

Table 3.16

Heteroscedasticity-Corrected Funnel Asymmetry Tests

Weighted by precision	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
1/SE (effect beyond bias)	0.004	0.078*	0.016	0.058**
Constant (Publication bias)	0.128	-3.138	-0.608	-2.241**
No of estimates	476	279	476	279
No of studies	25	17	25	17
Weighted by precision and No. of observations	**FE**	**FE_Published**		
1/SE (effect beyond bias)	0.014	0.054*		
Constant (Publication bias)	-1.044	-3.615**		
No of estimates	476	279		
No of studies	25	17		

Note. The table presents the results of heteroscedasticity-corrected FAT. Top panel presents weighted regressions by precision and the bottom panel presents weighted regressions by precision and number of observations. The standard errors are clustered at the study level. Fixed effects estimation uses study dummies and instrumental variable estimation uses logarithm of the number of observations as the instrumental variable. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

3.10 Conclusion

This chapter replicates Z&H's meta-analysis on how bank competition affects financial stability. It performs a pure replication using Z&H's dataset, and a verification of results conducted by re-coding the data using the same studies as Z&H. Both exercises confirm Z&H's conclusions: It finds that bank competition has only a small effect on financial stability (less than 0.07). In addition, it finds evidence of moderate, negative publication bias, consistent with journals discriminating in favor of studies that estimate a negative relationship between competition and stability.

There is great heterogeneity across studies that have examined this subject. As a result, this chapter investigates the extent to which study and data characteristics are systematically associated with estimated effect sizes. The large number of associated variables leads to the "model uncertainty problem"; i.e, there is uncertainty about the set of variables that should be included in an analysis of the determinants of effect sizes. Bayesian Model Averaging (BMA) provides an approach to handling this problem. Following Z&H, this chapter uses this approach, identifying a number of key contributing factors.

It finds that sample size, country coverage, types of measures for stability and competition, estimation method, and publication characteristics are the key determinants of heterogeneity in estimated effect sizes across studies. Large sample size tends to produce smaller competition estimates. The estimates from studies of developed countries are slightly larger compared to the estimates for developing and transition countries. Studies using a dummy variable to measure financial crises tend to estimate larger competition effects. Compared to other measures of competition, H-statistic is associated with larger estimated effects, and the Boone index with smaller effects. The analysis finds evidence that studies that use logit estimation are more likely to produce smaller estimates of competition effects.

Further, all the publication characteristics (citations, year publication first appeared, impact factor) have high posterior inclusion probabilities in the baseline results and subsequent robustness checks. These study and data characteristics help explain different estimated effect sizes across studies. However, the main finding from this chapter is that there is little evidence to support the view that competition in the banking sector plays a major role in countries' financial stability.

Chapter Four

4.1 Introduction

In recent years, a number of studies have assessed the relationship between bank competition and financial stability. These present conflicting findings on bank competition and financial stability. Some studies support the view that competition increases financial stability (Amidu & Wolfe, 2013; Ashraf, Ramady, & Albinali, 2016; Fiordelisi & Mare, 2014). While others find evidence that competition decreases financial stability (Ali, 2015; Amidu, 2013; Bretschger, Kappel, & Werner, 2012; Bushman, Hendricks, & Williams, 2016; Diallo, 2015). The previous chapter replicates the paper “Bank Competition and Financial Stability: Much Ado about Nothing?” (Zigraiova & Havranek, 2016). This chapter follows a similar line of Meta-Regression Analysis (MRA) and examines the findings from more recent studies of bank competition and financial stability. These include journal articles, working papers, and other studies that were not included in Zigraiova and Havranek’s (Z&H) sample.

This chapter applies the same empirical methodology and model specifications as Z&H to a different sample of studies to estimate how bank competition affects financial stability. It collects estimates of bank competition on financial stability from 35 studies[10]. Findings of the chapter indicate that there is a small effect (-0.009) of bank competition on financial stability, providing further support for Z&H’s conclusion. Further, they confirm that the heterogeneity in estimated effects reported in the literature are systematically related to the use of different measures for competition and stability, different country categories, and different methods for estimating the relationship between competition and stability. In addition, the analysis finds no evidence of publication bias in the recent literature.

[10] Appendix 4 gives a list of additional studies.

This chapter is organized as follows. Section 4.2 describes the dataset, section 4.3 explains the effect of bank competition on financial stability, and section 4.4 begins the analysis by testing for publication bias. Section 4.5 explores the determinants of effect heterogeneity in the literature. Section 4.6 applies Bayesian Model Averaging to address model uncertainty. Section 4.7 calculates a "best practice" estimate of the effect of competition on stability. Section 4.8 undertakes robustness checks. Section 4.9 estimates the relationship of bank competition and stability using linear estimates. Section 4.10 removes concentration measures and re-estimates the competition-stability relationship. Section 4.11 summarizes the main findings of the chapter.

4.2 The Dataset of Competition-Stability Estimates

Z&H used 31 studies for their MRA. This chapter collects additional studies on bank competition and financial stability. Extra studies were collected from the Google Scholar and RePEc search engines. Six keyword combinations were used to collect relevant studies: (i) Competition and stability; (ii) Competition and fragility/financial crisis; (iii) Concentration and stability; (iv) Concentration and fragility; (v) Market power and stability; and (vi) Market power and fragility. Of the 42 new studies found, 7 were eliminated as they did not report estimation results or standard error values (or any statistics relevant to calculating standard errors).

All studies estimate specifications of the following general form:

$$Stability = \alpha + \beta Competition\ Measure + error \tag{4.1}$$

When the study includes an interaction of competition with another control variable, the associated estimates are excluded from the sample. This is because the total effect is a linear combination of two coefficients. In addition to requiring statistical information about the control variable (usually the mean), one also needs to know the covariance of the respective coefficients in order to calculate the effect standard error. However, it does include estimates that use a quadratic specification of the competition variable, following the same procedure as Z&H whenever sufficient data were available.

Because the studies use specifications that make use of a wide variety of measures and functional forms, estimates were transformed to partial correlation coefficients (PCCs) to enable comparability (Doucouliagos, 2011). By converting estimates to a common scale of -1 to 1, the strength of association across estimates becomes comparable, which also allows investigation of their systematic determinants. The formulas for PCC and the standard error of PCC (SEPCC) are as follows:

$$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}}, \tag{4.2}$$

$$SEPCC_i = \sqrt{\frac{1 - PCC_i^2}{df_i}}, \tag{4.3}$$

where t is the t-statistic of the estimated coefficient, df is the degrees of freedom of the estimation, and i identifies the i^{th} estimated coefficient. The final sample consists of 762 estimates from 35 studies, most of which were published after 2010[11].

Figure 4.1 presents a scatter graph of estimates over time (specifically, the associated PCCs). The estimated PCC values are close to zero. Notably, they do not converge over time. The line shows a slightly positive linear relationship between the competition estimates and the year the study was first published.

[11] Data and codes to reproduce the results of the chapter are available on https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/IJGAXP or https://github.com/SamangiBandaranayake/Bank-Competition-and-Financial-Stability/tree/master/Chapter%20Four

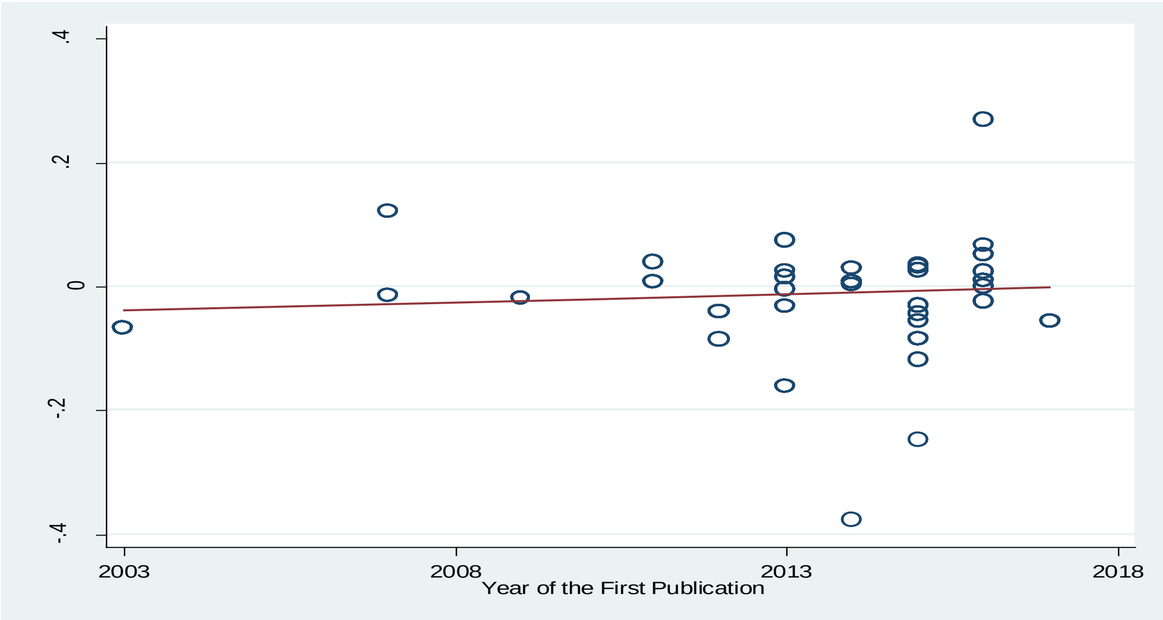


Figure 4.1. The Median PCC Estimates of Bank Competition and Financial Stability

Note. The horizontal axis measures the year when the studies appear in Google Scholar and the vertical axis represents median partial correlation coefficients corresponding to the effects of bank competition on financial stability. The line shows the linear fit.

4.3 The Effect of Bank Competition on Financial Stability

Beck (2008) presents a narrative survey of bank competition and financial stability that highlights the diversity on competition and stability in the literature. Researchers use various measures of competition and stability to estimate the relationship and there is no consistency in these measures.

One of the challenges in comparing estimates across studies is that some of the competition measures are increasing in the degree of greater competition, while others are decreasing. For example, a large value of the Lerner index implies less competition, while a large value of H-statistic implies high competition. A similar challenge arises with measures of financial stability. A large value of distance-to-default indicates more stability, while a large value of the non-performing loan ratio indicates less stability.

4.3.1 Variability of the estimated effects (PCCs)

The PCCs associated with the estimated competition effects range from -1 to +1. The smallest value is -0.8938 and the largest value is 0.9213. Figure 4.2 shows a box plot of the PCCs. It illustrates the variability of the estimated competition effects both within and across studies.

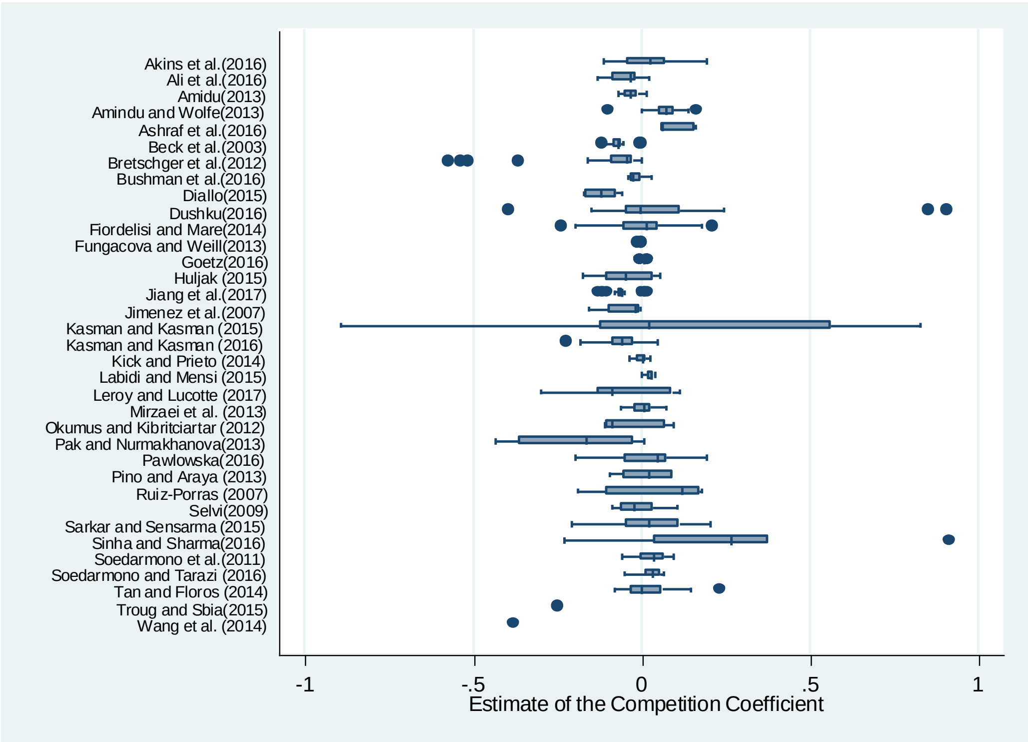


Figure 4.2. Variability in the Estimated Competition Effects (PCCs) by Individual Studies

While variability in the PCCs is evident, the majority of estimates are close to zero. Figure 4.3 illustrates the distribution of partial correlation coefficients. The values are distributed around zero. The mean value of PCCs from all estimates is -0.009 and the median value is -0.012. There are 27 published studies in the sample and the mean of PCCs from these is -0.008. This indicates that there is little difference between PCCs for published and unpublished studies, though this will be explored in further detail below.

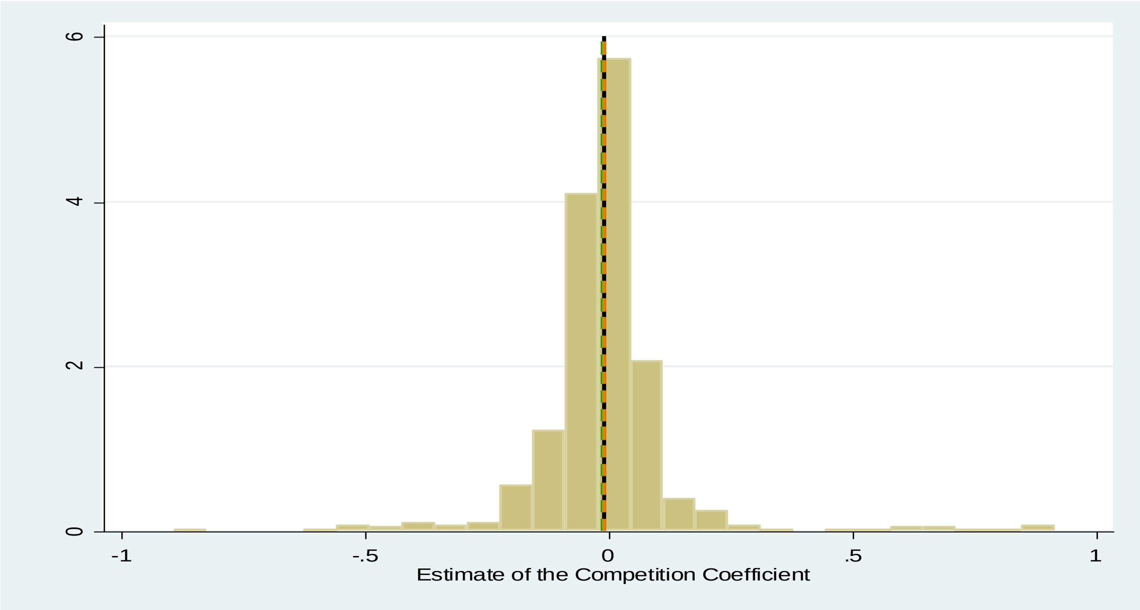


Figure 4.3. The Histogram of the Partial Correlation Coefficients

Note. The solid vertical line (black line) denotes mean of all PCCs. Two dash lines (green and orange lines) represent median of PCCs and mean of PCCs from published studies.

4.3.2 The effect of the competition

Table 4.1 reports the effect of competition on financial stability. Results are reported for three groups. The first row reports results for all 762 estimates from 35 studies ("All"). The second row reports estimates for studies that focused on countries from the Organisation for Economic Co-operation and Development (OECD), here equated with "Developed" countries. These comprise 333 estimates in total. The final row reports 185 estimates from "Developing and transition" (non-OECD) countries.

The left side of the table presents unweighted PCCs, and the right side of the table shows weighted PCCs estimates, for the three groups. The weighted estimates use weights based on the inverse of the number of estimates reported per study. Thus, whereas unweighted estimates weight each estimate the same, ceteris paribus, weighted estimates give greater (lesser) weight to estimates from studies that report a smaller (larger) number of estimates. This serves to assign equal weights to studies, as opposed to equal weights to estimates, so that studies that report more estimates do not have undue influence.

According to Doucouliagos (2011), PCC values less than 0.07 are considered “small”. By that measure, all the estimated effects other than the weighted estimates for Developing and transition countries are “small”. Further, all the estimated effects are statistically insignificant.

Table 4.1

Estimates of the Competition Effect for Different Country Groups

Country group	**Unweighted**			**Weighted**			**No of estimates**
	Mean	**95% CI**		**Mean**	**95% CI**		
All	-0.009	-0.029	0.010	-0.016	-0.052	0.019	762
Developed	-0.006	-0.033	0.021	-0.006	-0.036	0.024	333
Developing and transition	0.001	-0.037	0.039	-0.024	-0.118	0.069	185

Note. The table presents the mean PCCs of competition coefficient estimates for all estimates, estimates from developed (OECD) countries, and developing and transition (non-OECD) countries. The left side of the table presents, unweighted mean values and 95% confidence interval. The confidence intervals around the mean are constructed using standard errors clustered at the study level. In the right side of the table, estimates are weighted by the inverse number of estimates per study.

4.4 Testing for Publication Bias

Publication bias arises when editors, reviewers, and researchers give more prominence to statistically significant results and/or results that confirm theoretical priors (Stanley, 2007). This results in an over-representation of statistically significant/theoretically confirmatory results in the literature. Doucouliagos and Stanley (2013) find that publication bias exists in most of the empirical literature in economics and finance.

4.4.1 Funnel plots

Funnel plots are graphical tools to identify the presence of publication bias (Egger et al., 1997; Stanley, 2007). The horizontal axis reports the PCC value, and the vertical axis reports either the standard error of the PCC or its inverse (precision), with more precise estimates (estimates with smaller standard errors) reported at the top of the plot. When there is publication bias in the literature, the funnel plot is asymmetrical because the publication process favours estimates of one sign (or size) over those of another (Egger et al., 1997).

Figure 4.4 presents the funnel plot for PCCs using the full sample of estimates. Figure 4.5 calculates the median PCC value for each study and plots those. In the first figure, there is one point for each estimate. In the second figure, there is one point for each study. Both plots fail to uncover any evidence of publication bias, as the respective plots are symmetric around the mean value of PCCs.

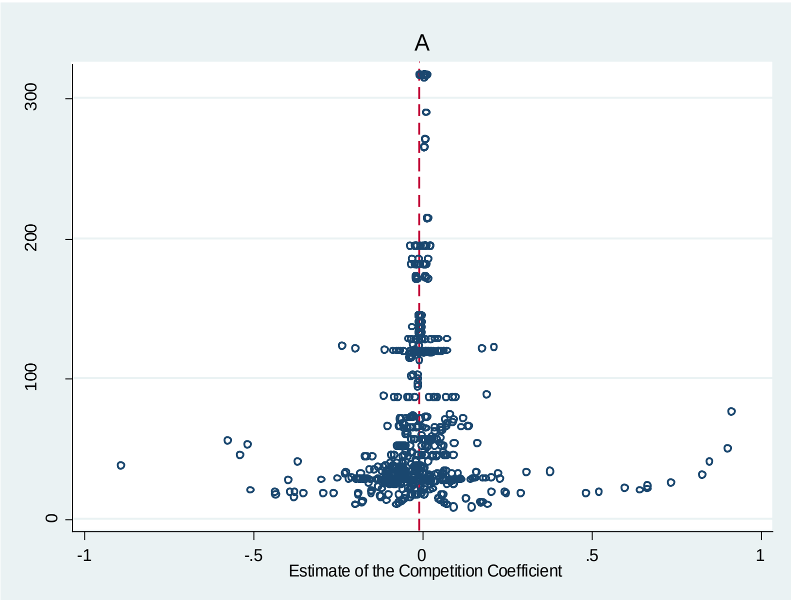


Figure 4.4. PCC of All Estimates

Note. The figure shows a funnel plot of the PCCs of the competition coefficient estimates. The size of the estimated effect is on the horizontal axis and precision on the vertical axis. The dashed vertical line denotes the mean value the PCCs of all the estimates.

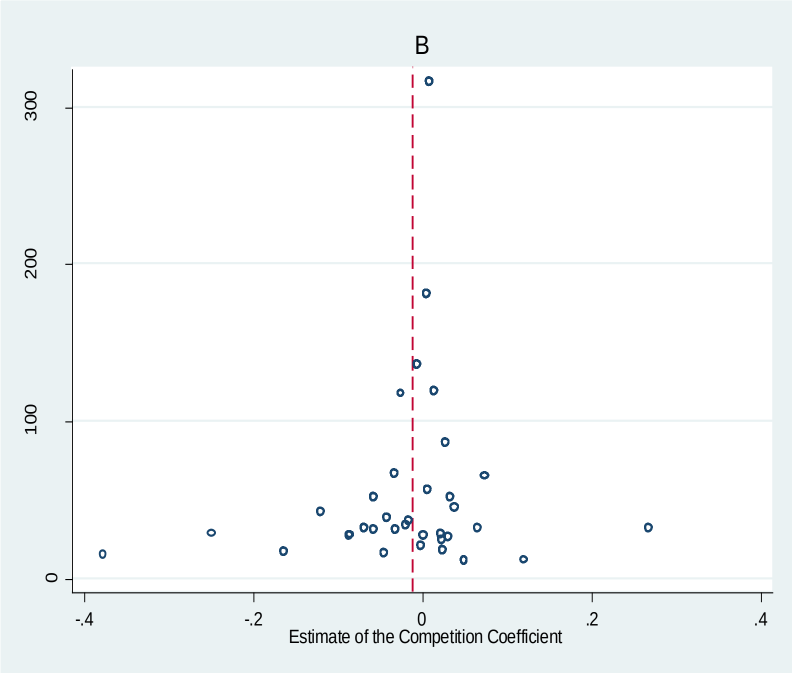


Figure 4.5. Median Values of PCC Estimates[12]

Note. The figure shows a funnel plot of the median values of PCCs of the competition coefficient estimates. The size of the estimated effect is on the horizontal axis and precision on the vertical axis. The dashed vertical line denotes the mean value the median PCCs of all the estimates.

[12] Large precision arises as a result of Study ID-44. This value is correct and there is no coding error.

Table 4.2

Funnel Asymmetry Tests

Panel A				
Unweighted Regressions	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
SE (Publication bias)	-1.837	-2.249	0.023	-0.112
Constant (effect beyond bias)	0.044	0.060	-0.010	-0.005
No of estimates	762	598	762	598
No of studies	35	27	35	27
Panel B				
Weighted Regressions	**FE**	**FE_Published**		
SE (Publication bias)	-1.512	-3.123		
Constant (effect beyond bias)	0.035	0.074		
No of estimates	762	598		
No of studies	35	27		

Note. The table presents the results of FAT. The standard errors are clustered at the study level. The panel A presents the unweighted regressions and panel B presents the weighted regressions. Fixed effects estimation uses study level fixed effects and for the instrumental variable estimation, logarithm of the number of observations uses as the instrumental variable.

4.4.2 Funnel asymmetry test

The Funnel Asymmetry Test (FAT) provides a more rigorous, statistical approach for testing for publication bias. It estimates the specification,

$$PCC_i = \beta_0 + \beta_1 SE\ (PCC)_i + \varepsilon_i\ , \qquad (4.4)$$

where PCC_i is the partial correlation coefficient of the competition coefficient, $SE(PCC_i)$ is the standard error of the PCC, β_0 is the mean PCC corrected for publication bias, β_1 measures the degree of publication bias, and ε_i is the error term. A test of publication bias consists of a test of the null hypothesis, H_0: $\beta_1 = 0$. Rejection of the null is interpreted as evidence of publication bias (Doucouliagos & Stanley, 2013; Egger et al., 1997; Stanley, 2007).

Table 4.2 above presents the results of the FAT. Panel A reports the results for the unweighted regressions. Following Z&H, the left side of the panel reports panel fixed effects estimation with standard errors clustered at the individual study level. The right side of panel A shows instrumental variable estimates, where the logarithm of the number of observations is used as the instrumental variable. Panel fixed effects estimation controls for study-specific characteristics, and instrumental variable estimation handles the endogeneity issue. The table also separates out studies that were published in peer-reviewed journals ("Published"). Following Z&H, only coefficient estimates are reported, without standard errors. Across both estimation methods and both samples (All and Published), the publication bias term ("SE – Publication Bias") is statistically insignificant at the 5-percent level. Therefore, the null hypothesis of no publication bias cannot be rejected.

Panel B reports the results from regressions weighted by the inverse of the number of estimates per study. This reduces the influence of studies reporting many estimates. Weights are not allowed in instrumental variable estimation. As a result, estimates are only reported for panel fixed effects estimation. The results of panel B are similar to the unweighted regression results of panel A, with all the associated publication bias terms being statistically insignificant.

One problem with the results in Table 4.2 is that the underlying specification of equation 4.4 is characterized by heteroscedasticity. To address this problem, Egger et al.

(1997) suggest an alternative specification for testing for publication bias. They propose the following specification:

$$t_i = \beta_1 + \beta_0 \left(1/SE(PCC_i)\right) + \mu_i \,, \tag{4.5}$$

where t_i is the PCC t-statistic, β_0 again measures mean PCC corrected for publication bias, and β_1 continues to measure the degree of publication bias.

Equation (4.5) is derived from Equation (4.4) by dividing the latter by $SE(PCC_i)$. This serves to correct the heteroscedasticity inherent in equation (4.4). OLS estimation of equation (4.5) produces efficient estimates of the parameters with consistent estimates of the associated standard errors. In the specification of equation (4.5), the independent variable is now the precision of the PCC estimate, and the intercept and slope coefficients are reversed from equation (4.4). The FAT is still carried out by testing $\beta_1 = 0$, with rejection of this hypothesis taken as evidence for the existence of publication bias. Table 4.3 reports heteroscedasticity-corrected FAT results. As before, the results are statistically insignificant across the board, in both panels. The interpretation is that there is no evidence to support the existence of publication bias. Table 4.3 also provides estimates of the publication bias-corrected, overall mean competition effect (cf. “1/SE – effect beyond bias”). With one exception, all the estimates show a small effect size, with the sole exception being the panel fixed effects estimate in Panel B. However, none of the estimates of the competition effect are statistically significant.

Table 4.3

Heteroscedasticity-Corrected Funnel Asymmetry Tests

Panel A				
Weighted by precision	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
1/SE (effect beyond bias)	0.030	0.025	-0.013	-0.008
Constant (publication bias)	-2.409	-1.918	0.837	0.222
No of estimates	762	598	762	598
No of studies	35	27	35	27
Panel B				
Weighted by precision and No. of observations	**FE**	**FE_Published**		
1/SE (effect beyond bias)	0.150	0.053		
Constant (publication bias)	-8.191	-3.282		
No of estimates	762	598		
No of studies	35	27		

Note. The table presents the results of heteroscedasticity-corrected FAT. The standard errors are clustered at the study level. Panel A presents the weighted regressions by precision and panel B presents the weighted regressions by precision and number of observations. Fixed effects estimation uses study level fixed effects and for the instrumental variable estimation, logarithm of the number of observations uses as the instrumental variable.

4.5 Heterogeneity

To investigate heterogeneity in the literature, this study employs 35 variables to categorize each estimate/study. The definitions of these variables are provided in Appendix 3. Table 4.4 reports the mean, standard deviation, and weighted mean for each variable, where the weight consists of the inverse of the number of estimates per study. All variables are categorized into eight groups: data characteristics, countries examined, design of the analysis, treatment of stability, treatment of competition, estimation method, control variables, and publication characteristics.

Group 1: Data characteristics

The variables grouped into "Data characteristics" consist of PCC, the standard error of the PCC ("SEPCC"), the logarithm of the number of observations used in the regression ("Samplesize"), the logarithm of number of years in the sample period ("T"), and mean year of the sample period ("Sampleyear").

Group 2: Countries examined

One possible reason why competition effects differ across studies is that the effect of competition may differ across countries depending on their degree of economic and financial development. Accordingly, estimates/studies are divided into three groups depending on the countries that were included in the samples of the respective studies. Dummy variables are created for developed (OECD) countries, developing and transition countries (non-OECD), and for a mixed category, consisting of both developed, and developing and transition countries. 44 percent of the estimates are from OECD countries; whereas, 24 percent of the estimates are from non-OECD countries and 32 percent belong to the mixed category.

Group 3: Design of the analysis

Studies also differ in their design. To capture the variation in design, this study uses four dummy variables. The dummy variable "Quadratic" distinguishes linear and non-linear estimates. Table 4.4 reports that 6 percent of the estimates are based on a non-linear relationship between competition and stability. "Endogeneity" equals 1 if the estimation method used to produce the estimate corrected for endogeneity. Approximately 70 percent of the estimates attempted to correct endogeneity. Some regressions used aggregated country level data rather than bank- or sub-national data. The variable “Macro” takes the value 1 when country-level data were used. 16 percent of the estimates were based on aggregated country-level data. “Averaged” indicates that the respective competition/stability data were averaged bank-level data. This applies to only a very small number of estimates, approximately 1 percent.

Group 4: Treatment of stability

There is no commonly accepted measure of financial stability in the literature. To address this heterogeneity, and to investigate whether how one measures stability affects estimates of the competition effect, measures are grouped into seven categories. Z-score is a popular measure, with 27 percent of the estimates coming from specifications where Z-score was used as the dependent variable in a study of competition and financial stability. Other common measures of financial stability are the non-performance loan ratio (“NPL”) and a dummy variable that takes the value 1 when the banking system has suffered a systemic crisis (“Dummies”). These account for 16 and 21 percent of estimates, respectively. The reference group captures other stability measures not included in the previous categories. Examples include interest margin, liquidity risk, and costs to assets (Akins, Li, Ng, & Rusticus, 2016; Ali, 2015; Huljak, 2015; Tabak, Gomes, & da Silva Medeiros, 2015). A substantial number of estimates, approximately 21 percent, use these alternative measures.

Group 5: Treatment of competition

Like financial stability, many different measures are used to gauge the degree of competition in the banking sector. These are categorized by five dummy variables. The most popular measure of competition is the Lerner index. 36 percent of the estimates come from regressions that use this measure. The next most popular measure is the Concentration share, which serves as the competition measure for 24 percent of the estimates in the sample.

Group 6: Estimation method

A variety of estimation methods are used to study the relationship between competition and stability. It is possible that estimation method is systematically associated with estimates of the competition effect. To investigate this, the different estimation methods are represented by six dummy variables: Logit, Ordinary Least Squares (OLS), panel fixed effects, panel random effects, Generalized Method of Moments (GMM), and two-stage least squares. Thirty one percent of the estimates derive from panel fixed effects, 23 percent from GMM, 12 percent from Logit estimation, and 11 percent from panel random effects.

Group 7: Control variables

When estimating the competition-stability relationship, studies hold constant a variety of control variables to address omitted variable bias. Of these, three sets of control variables are relatively common. One concern is that the regulatory and supervisory environment can affect the estimate of the competition effect ("Regulation"). 9 percent of estimates come from regressions that control for these factors. The ownership nature of the bank (e.g., state-owned) may also play a role. 10 percent of estimates come from regressions that include these variables. Most commonly, studies attempt to control for the macroeconomic conditions of the economies they are studying ("Global"). 68 percent of estimates come from regressions where some kind of macroeconomic control variables are included.

Group 8: Publication characteristics

It stands to reason that the quality of a study could affect estimates of the competition effect. Several variables are included to control for quality. These are the number of citations received by the article from which the estimate comes, the year the study first appeared in Google Scholar (“Firstpub”), the journal’s RePEc (recursive) impact factor, and whether the study was published in peer-reviewed journal.

Table 4.4

Overview and Summary Statistics of Regression Variables

Variable	Mean	SD	WMean
Data characteristics			
PCC	-0.009	0.134	-0.016
SEPCC	0.029	0.024	0.034
Samplesize	7.779	1.848	7.247
T	2.425	0.615	2.352
Sampleyear	9.644	6.076	10.509
Countries examined			
Developed	0.437	0.496	0.324
Developing and transition	0.243	0.429	0.343
Reference case: Mixed	0.320	0.467	0.333
Design of the analysis			
Quadratic	0.060	0.238	0.137
Endogeneity	0.693	0.462	0.520
Macro	0.163	0.370	0.143
Averaged	0.012	0.108	0.004
Treatment of stability			
Dummies	0.211	0.408	0.149
NPL	0.160	0.370	0.199
Z_score	0.270	0.444	0.335
Profit volatility	0.039	0.195	0.054
Profitability	0.058	0.233	0.041
Capitalization	0.029	0.168	0.027
DtoD	0.024	0.152	0.009
Reference case: other stability	0.209	0.407	0.185

Variable	Mean	SD	WMean
Treatment of competition			
H-statistic	0.039	0.195	0.056
Boone	0.038	0.191	0.040
Concentration	0.244	0.430	0.213
Lerner	0.357	0.479	0.357
HHI	0.139	0.346	0.200
Reference: other competition	0.182	0.386	0.133
Estimation method			
Logit	0.119	0.324	0.090
OLS	0.093	0.291	0.173
FE	0.315	0.465	0.267
RE	0.108	0.310	0.081
GMM	0.232	0.423	0.263
TSLS	0.056	0.231	0.041
Reference: other method	0.076	0.265	0.087
Control variables			
Regulation	0.089	0.285	0.100
Ownership	0.102	0.303	0.149
Global	0.678	0.467	0.740
Publication characteristics			
Citations	0.643	0.516	0.599
Firstpub	10.571	3.056	10.429
IFrecursive	0.108	0.134	0.085
Reviewed journal	0.785	0.411	0.771

Note. The table presents summary statistics of regression variables. SD is the standard deviation and WMean is the mean weighted by the inverse of the number of estimates reported per study.

4.6 Bayesian Model Averaging

In a meta-regression analysis (MRA), the estimated effect sizes are regressed on estimate and study characteristics in order to identify and measure the influence of systematic determinants. However, given the large number of variables typically involved in an MRA, there is a large degree of uncertainty about the "true" specification. While all possible variables could be included in an MRA, substantial multicollinearity is inevitable, making it difficult to identify significant determinants. For this reason, a number of meta-analysts have turned to Bayesian Model Averaging (BMA).

There are 35 explanatory variables in this study (refer Appendix 3 for detailed descriptions of the variables). BMA runs multiple regressions with different subsamples of the 2^{35} possible combinations of explanatory variables. BMA reports the posterior mean and standard deviation by calculating a weighted average value from each estimation model, with weights calculated from the respective likelihood of the given regression model. BMA also calculates the posterior inclusion probability (PIP). The PIP can be interpreted as the probability that a specific variable belongs in the "true" model. Eicher et al. (2011) provide some guidelines on how to interpret the strength of a relationship based on the PIP value. PIP values between 0.50 and 0.75 are considered weak. PIP values between 0.75 and 0.95 are considered substantial. PIP values between 0.95 and 0.99 are considered strong. And PIP values that exceed 0.99 are considered decisive.

Table 4.5 reports the results of the BMA analysis, where the respective regressions are weighted by the inverse number of estimates per study. The left side of the table reports the BMA analysis. For this analysis, the following parameters were chosen: For the "unit information prior", Zellner's g-prior was selected. This is the default prior in BMA (Zeugner & Feldkircher, 2015). In addition, a uniform model prior is selected (Zeugner & Feldkircher, 2015).

The BMA analysis is used to select an amalgamated "best model." Another approach consists of estimating the MRA using OLS. The middle three columns of the Table 4.5 report results of the MRA using OLS estimation. The included explanatory variables were selected on the basis of having PIP values greater than 0.5. A comparison of the BMA and OLS results reveals generally similar estimates in both sign and size. The exception is the variable "Sampleyear".

The last three columns on the right side of the table report OLS estimates of the MRA where variable selection is based on the variables Z&H used in their analysis (Zigraiova & Havranek, 2016). These estimates are not so similar to the BMA and prior OLS estimates. This suggests that the variables important for explaining heterogeneity in the estimated effects in the supplementary sample of estimates are not the same as the determinants in Z&H sample of estimates.

For example, the BMA analysis calculates a PIP of SEPCC of 0.0260. This indicates a very small degree of publication bias. This contrasts with the OLS results from the last three columns of the table. The difference is due to the specification of the model. In this case, the OLS results appear spurious, driven by omitted variable bias caused by the omission of important variables as indicated in the BMA analysis.

In fact, the BMA analysis identifies relatively few important determinants of competitive effects, where importance is measured by the respective PIPs. According to the BMA analysis, an increase in the duration of the sample period (T) by one year reduces the effect of competition by 0.04. Estimates for developed countries tend to produce more negative estimates of competition effects than estimates for mixed countries. Likewise, studies that employ country-level data ("Macro") tend to find less evidence that competition enhances stability. The BMA estimates indicate that estimates based on country-level data have PCC estimates that are 0.13 less than other estimates.

BMA also identifies Z-score as an important determinant of estimated competition effects, with a PIP of 0.9026. The posterior mean estimate indicates that studies using this measure for financial stability have PCC values 0.05 less than studies using one of the measures included in the reference category of miscellaneous, other measures of stability. Concentration is the only competition measure with a decisive PIP. BMA estimates that PCC values are 0.13 higher for studies using this measure of competition. According to Doucouliagos (2011), this is a “medium” size effect. BMA also identifies HHI as an important competition measure.

A number of estimation methods are identified by the BMA analysis as being important. Logit, OLS, panel fixed effects, and panel random effects are all associated with generally lower PCC values. Number of citations, year the study first appeared in Google Scholar, and whether the study was published in a peer-reviewed journal are important quality measures. The associated latter estimate indicates that studies that are published in peer-reviewed journals produce PCC estimates approximately 0.22 lower than other studies.

Table 4.5

Explaining Heterogeneity in the Estimates of the Competition Coefficient

Variable	**Bayesian model averaging**			**OLS**			**OLS (Z&H's variable selection criteria)**		
	Post. mean	**Post. SD**	**PIP**	**Coeff**	**Robust SE**	**p-value**	**Coeff**	**Robust SE**	**p-value**
Data characteristics									
SEPCC	0.0028	0.0715	0.0260				-2.1946	1.9596	0.263
Samplesize	-0.0003	0.0025	0.0395				-0.0341	0.0274	0.212
T	-0.0446	0.0228	0.9060	-0.0238	0.0246	0.335			
Sampleyear	-0.0034	0.0037	0.5321	0.0017	0.0034	0.624			
Countries examined									
Developed	-0.0776	0.0311	0.9335	-0.0351	0.0291	0.227	-0.0284	0.0400	0.478
Developing and transition	0.0046	0.0151	0.1159				-0.0013	0.0365	0.972
Design of the analysis									
Quadratic	0.0084	0.0205	0.1845				0.0092	0.0657	0.889
Endogeneity	-0.0180	0.0317	0.3042						
Macro	-0.1327	0.0405	0.9797	-0.0874	0.0342	0.011			
Averaged	0.0001	0.0243	0.0174						
Treatment of stability									
Dummies	0.0577	0.0604	0.5488	0.0410	0.0325	0.208	0.0403	0.0399	0.313

Variable	**Bayesian model averaging**			**OLS**			**OLS (Z&H's variable selection criteria)**		
	Post. mean	**Post. SD**	**PIP**	**Coeff**	**Robust SE**	**p-value**	**Coeff**	**Robust SE**	**p-value**
NPL	0.0026	0.0118	0.0744						
Z_score	-0.0487	0.0222	0.9026	-0.0326	0.0300	0.277			
Profit volatility	0.0036	0.0151	0.0772						
Profitability	-0.0264	0.0483	0.2762						
Capitalization	-0.0009	0.0087	0.0270						
DtoD	-0.0028	0.0274	0.0268						
Treatment of competition									
H-statistic	0.0030	0.0130	0.0763				0.0396	0.0667	0.552
Boone	-0.0162	0.0362	0.2110				-0.1164	0.0578	0.044
Concentration	0.1293	0.0218	1.0000	0.1001	0.0286	0.000			
Lerner	-0.0009	0.0093	0.0559						
HHI	0.0637	0.0193	0.9729	0.0751	0.0495	0.129			
Estimation method									
Logit	-0.1681	0.0590	0.9976	-0.0842	0.0445	0.058	-0.0817	0.0378	0.031
OLS	-0.2274	0.0297	1.0000	-0.1497	0.0523	0.004	-0.1297	0.0536	0.576
FE	-0.0797	0.0342	0.9507	-0.0359	0.0291	0.217			
RE	-0.0981	0.0442	0.9451	-0.0390	0.0398	0.327			
GMM	0.0019	0.0115	0.0565						

Variable	**Bayesian model averaging**			**OLS**			**OLS (Z&H's variable selection criteria)**		
	Post. mean	**Post. SD**	**PIP**	**Coeff**	**Robust SE**	**p-value**	**Coeff**	**Robust SE**	**p-value**
TSLS	-0.0014	0.0111	0.0390						
Control variables									
Regulation	-0.0003	0.0062	0.0245				-0.0216	0.0386	0.576
Ownership	-0.0121	0.0216	0.2876						
Global	0.0478	0.0338	0.7562	0.0421	0.0370	0.255			
Publication characteristics									
Citations	0.1456	0.0174	1.0000	0.1008	0.0356	0.001	0.0840	0.0253	0.001
Firstpub	0.0215	0.0048	1.0000	0.0135	0.0045	0.003	0.0137	0.0064	0.032
IFrecursive	0.0227	0.0670	0.1376				0.1760	0.1119	0.116
Reviewed journal	-0.2189	0.0209	1.0000	-0.1502	0.0481	0.002	-0.1226	0.0505	0.015
Constant	0.0023	NA	1.0000	-0.0563	0.0836	0.501	0.2280	0.2378	0.337
Studies			35			35			35
Observations			762			762			762

Note. First three columns present results from Bayesian model averaging. OLS estimation includes explanatory variables with PIP greater than 0.5. OLS (Z&H's variable selection criteria) includes explanatory variables from Table 3.5.1 (page 93). The standard errors are clustered at the study level. Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. The inverse number of estimates per study is taken as the weight.

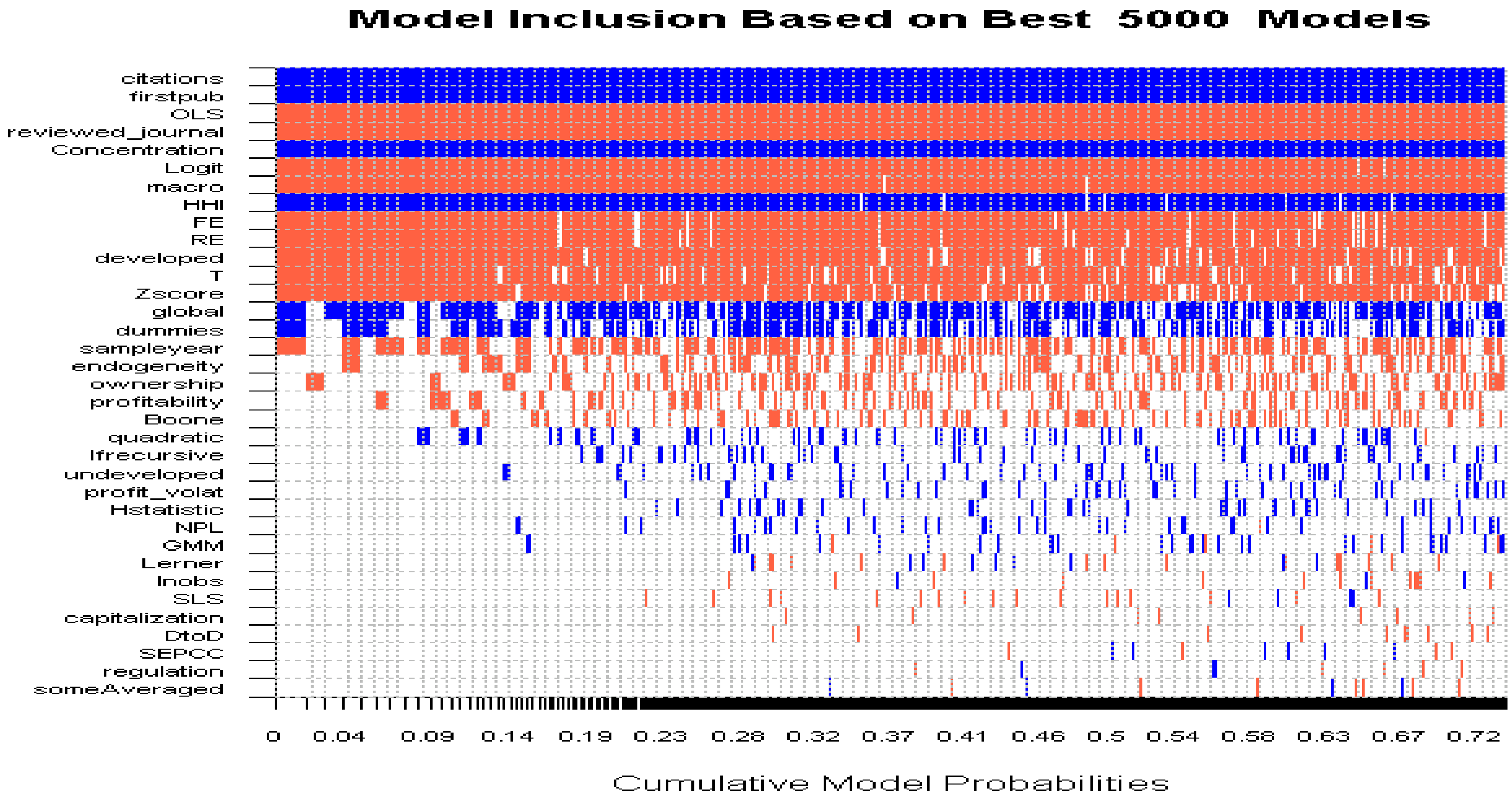


Figure 4.6. Bayesian Model Averaging – Model Inclusion Probability
Note. The figure illustrates results of BMA exercise. Columns represent individual models and rows represent explanatory variables. Explanatory variables are sorted by their PIP in descending order. The positive coefficient sign denoted by blue color, negative coefficients in red color and the excluded variables from a model is left blank.

Figure 4.6 gives a different perspective of the BMA results of Table 4.5. It provides a graphical representation of how frequently each of the 35 variables appear in the top 5000 models, where a model is defined as a unique variable combination. These 5000 models, out of 2^{35} models, account for a cumulative inclusion probability of 72 percent.

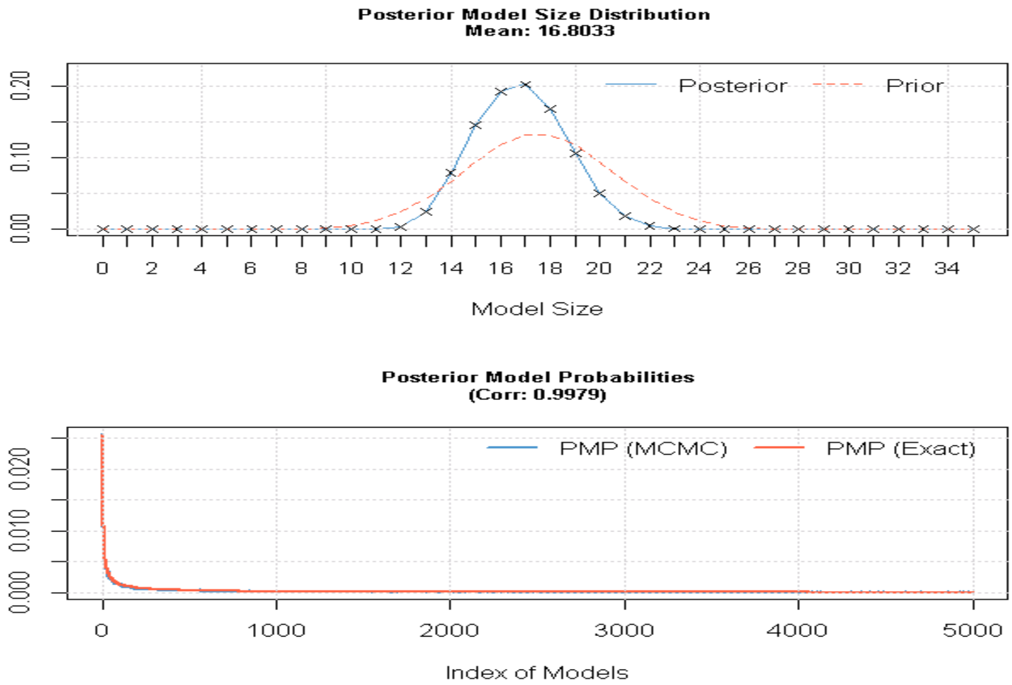


Figure 4.7. Distribution of Model Sizes and Probabilities of Top 5000 Models

The top figure of Figure 4.7 illustrates that, on average, there are 17 regressors in a model. This corresponds to the BMA analysis of Table 4.5, where it is seen that 17 variables have a PIP greater than 0.50. The bottom figure rank orders the top 5000 models in terms of their “model probability”, which can be loosely interpreted as the probability that a given model is “true”. A relatively small number of models have model probabilities larger than 0.001.

4.7 Best Practice Estimate of the Competition Effect

This section produces an estimate of the competition effect conditional on "best practice" estimation methods, where "best practice" is a subjective selection of data/study characteristics believed to produce the most reliable estimate of the competition-stability relationship. The best practice estimate is the predicted value of the PCC, based upon a given MRA estimated equation. With the associated variables set to their "best practice" values .

Table 4.6 reports best practice estimates for each of the three country samples in two panels. Each panel reports the best practice estimate of PCC ("Estimate"), its 95% confidence interval, and the difference with the unconditional PCC mean reported in Table 4.1 ("Diff"). Panel A reports best practice estimates using the variables selected by Z&H (2016). The left hand side of the panel uses the (weighted) OLS coefficient estimates from Table 4.5. The right hand side of the panel uses the (unweighted) OLS coefficient estimates from Table 4.8 below.

All the best practice estimates in panel A are statistically insignificant and very small. Taking 0.07 as the measure of "small" (Doucouliagos, 2011), all the estimates come in well below that. This indicates that the best estimates of the competition effect are negligible, not only in terms of statistical significance, but also in terms of economic size. The only caveat to this is the 95% confidence intervals based on the weighted estimates display a wide range that includes values that achieve "moderate" in size. Despite the efforts spent to improve on the unconditional estimates of mean PCC, neither the weighted nor unweighted best practice estimates – using Z&H's variables – resulted in much difference from the numbers reported in Table 4.1 (cf. "Diff").

Panel B also reports best practice PCC estimates, but these are based on the variables selected by the BMA analysis associated with Tables 4.5 (weighted) and 4.8 (unweighted).

Variables having a PIP greater than 0.50 in those tables were selected for the subsequent best practice calculations. As before, both weighted and unweighted regression coefficients were used to calculate the estimates.

The first thing to note from panel B is that the estimates are larger. This is not surprising, because these variables were chosen precisely because BMA analysis had determined that they were important for explaining the observed heterogeneity in PCC values. In contrast, the Z&H variables were based on an entirely different sample of studies. As is clear from Tables 4.5 and 4.8, BMA chose very different variables for this new set of additional studies.

Using the weighted OLS estimates from Table 4.5 produces best practice PCC estimates that range from 0.123 to 0.160 for the three different country groups. These values are moderate in size, and each of the estimates are significant at the 5 percent level. They suggest that competition is positively related to financial stability.

A different story emerges if one uses the unweighted OLS estimates from Table 4.8. The associated regression coefficients produce best practice estimates that are moderate in size, but take on negative values ranging from -0.207 to -0.215. All are significant at the 5 percent level. These estimates indicate that competition in the banking sector is negatively related to financial stability. Thus, on the one hand, the best practice estimates indicate that the effect of competition on financial stability is larger than indicated by the unconditional mean of PCC values. On the other hand, the sign of the estimates depend on the estimation procedure used to derive the respective coefficient estimates. An approach that weights studies equally leads to the conclusion that the relationship is positive. Alternatively, if one weights estimates equally, one concludes that there is a negative relationship.

Table 4.6

Best-Practice Estimates of the Competition Coefficient

Best Practice	**Weighted**				**Unweighted**			
	Estimate	**95 % CI**		**Diff**	**Estimate**	**95 % CI**		**Diff**
				Panel A - Variable selection is based on Z&H's criteria				
All	0.015	-0.217	0.248	0.031	0.002	-0.080	0.084	0.011
Developed	-0.003	-0.203	0.196	0.003	0.002	-0.071	0.075	0.008
Developing and transition	0.024	-0.237	0.285	0.048	0.001	-0.100	0.102	0.000
				Panel B - Variable selection is based on Table 4.5 and 4.8				
All	0.147***	0.041	0.254	0.163	-0.215***	-0.379	-0.052	-0.206
Developed	0.123**	0.026	0.221	0.129	-0.207***	-0.361	-0.052	-0.201
Developing and transition	0.160**	0.027	0.293	0.184	-0.215**	-0.392	-0.039	-0.216

Note. The table presents the mean PCCs of competition coefficient estimates for all pooled competition coefficient estimates, those from developed (OECD) countries, and those from developing and transition (non-OECD) countries. The left side of the table reports weighted estimates by inverse number of estimates per study. The right side of the table presents unweighted mean PCCs of competition coefficient estimates. Panel A reports the mean PCCs based on the variable selection used by Zigraiova and Havranek (2016). Panel B reports mean PCCs from variables with PIP > 0.5, from Table 4.5 and Table 4.8. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

4.8 Robustness Checks

This analysis follows Z&H (2016) and performs four robustness checks. Firstly, the BMA analysis is re-conducted with alternative priors. Secondly, BMA is completed using unweighted variables. Thirdly, OLS and panel fixed effects model are used to estimate a regression specification in which all variables are included. Finally, an alternative weighted least squares estimator is used that weights on the inverse of the variance of the estimated PCC.

4.8.1 Alternative priors

This section focuses on using a different g-prior and model prior for the BMA analysis. It then repeats the analysis of Table 4.5, except that it selects variables from this alternative BMA analysis and calculates best practice estimates using the corresponding OLS estimates. The results are reported in Table 4.7, where the alternative BMA analysis uses the benchmark prior (BRIC) instead of Zellner's g-prior and random for the model prior.

The left side of Table 4.7 reports the BMA results, and the right side of the table reports the corresponding OLS estimation. The OLS regression includes 14 variables calculated by BMA to have PIPs greater than 0.50. The OLS regression coefficients are similar to the BMA Posterior Mean estimates in both size and sign. The PIP of SEPCC is negligible, consistent with there being no publication bias in the literature.

The BMA results of Table 4.7 are similar to the baseline results of Table 4.5. The main difference is that the variables "Dummies" and "Sampleyear" have PIPs greater than 0.50 in Table 4.5 but not in Table 4.7. As a result, the OLS estimation in Table 4.7 uses 14 variables instead of 16. The resulting, estimated coefficients and associated statistical significances are similar to the baseline estimates in Table 4.5. This provides some evidence that employing alternative priors for the BMA analysis does not substantially change the baseline results of the study.

Table 4.7

Results with Alternative BMA Priors

Response variable	**Bayesian model averaging**			**OLS**		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-0.0004	0.0592	0.0186			
Samplesize	-0.0002	0.0020	0.0284			
T	-0.0372	0.0239	0.8264	-0.0318	0.0220	0.149
Sampleyear	-0.0019	0.0032	0.3076			
Countries examined						
Developed	-0.0778	0.0341	0.9040	-0.0372	0.0299	0.213
Developing and transition	0.0052	0.0170	0.1104			
Design of the analysis						
Quadratic	0.0053	0.0174	0.1171			
Endogeneity	-0.0121	0.0272	0.2148			
Macro	-0.1256	0.0437	0.9534	-0.0813	0.0374	0.030
Averaged	0.0000	0.0206	0.0123			
Treatment of stability						
Dummies	0.0324	0.0523	0.3233			
NPL	0.0012	0.0084	0.0413			
Z_score	-0.0556	0.0225	0.9293	-0.0341	0.0303	0.261
Profit volatility	0.0023	0.0122	0.0503			
Profitability	-0.0176	0.0412	0.1864			
Capitalization	-0.0007	0.0076	0.0197			
DtoD	-0.0021	0.0237	0.0193			
Treatment of competition						
H-statistic	0.0017	0.0098	0.0467			
Boone	-0.0141	0.0362	0.1665			

Response variable	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Concentration	0.1269	0.0225	0.9998	0.0975	0.0293	0.001
Lerner	-0.0018	0.0102	0.0576			
HHI	0.0609	0.0204	0.9533	0.0766	0.0495	0.122
Estimation method						
Logit	-0.1452	0.0573	0.9784	-0.0581	0.0315	0.065
OLS	-0.2287	0.0301	1.0000	-0.1519	0.0521	0.004
FE	-0.0730	0.0353	0.9117	-0.0380	0.0313	0.224
RE	-0.0826	0.0462	0.8685	-0.0249	0.0400	0.533
GMM	0.0017	0.0103	0.0492			
TSLS	-0.0004	0.0083	0.0238			
Control variables						
Regulation	-0.0002	0.0057	0.0191			
Ownership	-0.0116	0.0216	0.2655			
Global	0.0348	0.0348	0.5749	0.0404	0.0350	0.249
Publication characteristics						
Citations	0.1423	0.0174	1.0000	0.1014	0.0300	0.001
Firstpub	0.0195	0.0044	1.0000	0.0136	0.0041	0.001
IFrecursive	0.2074	0.0646	0.1196			
Reviewed journal	-0.2192	0.0216	1.0000	-0.1472	0.0485	0.002
Constant	0.0022	NA	1.0000	-0.0184	0.0827	0.824
Studies			35			35
Observations			762			762

Note. The table presents results of BMA exercise and OLS estimation. Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. OLS estimation includes explanatory variables with PIP greater than 0.5. The standard errors are clustered at the study level. The inverse number of estimates per study is taken as the weight.

4.8.2 Unweighted regressions

The second robustness check uses the same priors in the BMA analysis but does not weight the included variables. The baseline results of Table 4.5 weighted the variables by the inverse of the number of estimates per study. In these unweighted regressions, the results are dominated by the studies with many competition coefficient estimates. As previously, the left side of the table reports BMA results and the right side reports the corresponding OLS estimation – first using variables with PIPs greater than 0.50 from the BMA analysis, then using the same variables selected by Z&H in their analysis.

The first OLS regression includes 6 variables, compared to the 16 variables that were included in the baseline estimation. The PIP value of SEPCC is slightly less than 0.5, thus classifying it as a weak effect according to (Eicher et al., 2011). This supports the baseline finding of no publication bias in the literature. While the second set of OLS results include SEPCC, the associated coefficient estimate and p-value (0.970) show that there is a reason why the BMA analysis gave it such a low PIP. This further substantiates the conclusion of no publication bias.

Table 4.8

Results for Unweighted Regressions

Response Variable	**Bayesian model averaging**			**OLS**			**OLS (Z&H's variable selection criteria)**		
Competition Effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Data characteristics									
SEPCC	-0.4471	0.4942	0.4998				-0.0354	0.9455	0.970
Samplesize	0.0053	0.0070	0.4217				0.0035	0.0122	0.777
T	0.0005	0.0035	0.0349						
Sampleyear	0.0044	0.0019	0.9473	0.0026	0.0014	0.062			
Countries examined									
Developed	0.0000	0.0016	0.0141				-0.0007	0.0206	0.973
Developing and transition	-0.0000	0.0014	0.0122				-0.0014	0.0212	0.948
Design of the analysis									
Quadratic	0.0012	0.0077	0.0392						
Endogeneity	-0.0002	0.0026	0.0208						
Macro	-0.0006	0.0049	0.0305						
Averaged	-0.0000	0.0048	0.0107						
Treatment of stability									
Dummies	0.0003	0.0028	0.0207				-0.0114	0.0209	0.956
NPL	0.0551	0.0197	0.9619	0.0331	0.0213	0.120			

Response Variable	Bayesian model averaging			OLS			OLS (Z&H's variable selection criteria)		
Competition Effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Z_score	-0.0001	0.0020	0.0153						
Profit volatility	0.0000	0.0028	0.0115						
Profitability	-0.0103	0.0218	0.2223				-0.0697	0.0220	0.002
Capitalization	-0.0052	0.0179	0.0998						
DtoD	-0.0701	0.0507	0.7352	-0.1000	0.0129	0.000			
Treatment of competition									
H-statistic	0.0127	0.0272	0.2151				0.0664	0.0294	0.024
Boone	-0.0568	0.0494	0.6486	-0.0643	0.0553	0.245			
Concentration	0.0064	0.0158	0.1809						
Lerner	-0.0158	0.0224	0.3759						
HHI	0.0463	0.0316	0.7495	0.0567	0.0457	0.215			
Estimation method									
Logit	0.0000	0.0020	0.0121				-0.0158	0.0232	0.495
OLS	-0.0037	0.0125	0.1057						
FE	-0.0003	0.0028	0.0226				-0.0181	0.0202	0.371
RE	0.0002	0.0030	0.0171						
GMM	-0.0088	0.0168	0.2530						
TSLS	0.0006	0.0049	0.0305				-0.0027	0.0241	0.909

Response Variable	**Bayesian model averaging**			**OLS**			**OLS (Z&H's variable selection criteria)**		
Competition Effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Control variables									
Regulation	-0.0000	0.0019	0.0112						
Ownership	0.0001	0.0020	0.0123				0.0235	0.0465	0.613
Global	0.0003	0.0028	0.0246						
Publication characteristics									
Citations	-0.0001	0.0017	0.0156				0.0087	0.0197	0.659
Firstpub	0.0004	0.0013	0.1027				0.0045	0.0024	0.064
IFrecursive	-0.0696	0.0742	0.5348	-0.0472	0.0536	0.379	-0.0514	0.0606	0.396
Reviewed journal	-0.0044	0.0132	0.1259						
Constant	-0.0787	NA	1.0000	-0.0379	0.0156	0.015	-0.0751	0.1144	0.512
Studies			35			35			35
Observations			762			762			762

Note. This table presents results from unweighted regressions. First three columns present results from Bayesian model averaging. OLS estimation includes explanatory variables with PIP greater than 0.5. OLS (Z&H's variable selection criteria) includes explanatory variables from Table 3.8.1 (page 114). The standard errors are clustered at the study level. Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability.

4.8.3 Frequentist methods

The third robustness check follows a different approach. It includes all 35 variables. Estimation of the respective coefficients is done first with pooled OLS, then with panel fixed effects. The panel fixed effects method attributes any differences between studies to the intercept, imposing a common slope coefficient (Halcoussis, 2005).

Table 4.9 reports the results. The left side of the table shows the pooled OLS estimates, and the right side shows the panel fixed effects estimates. The panel fixed effects estimation omits five variables from the estimation equation (Macro, Citations, Firstpub, IFrecursive, and Reviewed journal), because these are the same for all estimates from the same study, and thus cannot be included with study fixed effects.

The coefficient values of SEPCC are statistically insignificant and support previous conclusions of no publication bias. Overall, the results of the pooled OLS estimation are similar to the baseline results of Table 4.5. Profitability, distance-to-default (DtoD), Concentration, OLS estimation, controls for macroeconomic variables (Global), the number of citations, year of first publication, and study published in a reviewed journal are statistically significant at the 5 percent level.

In contrast, the panel fixed effects results are somewhat different from both the pooled OLS and baseline OLS results. For the panel fixed effects model, Endogeneity, Profitability, Capitalization, distance-to-default, OLS, and GMM are statistically significant. Studies that control for endogeneity are estimated to have competition effects (PCCs) that are 0.07 larger than studies that do not control for endogeneity. Studies that measure financial stability using profitability, capitalization, or distance-to-default measures are more likely to find that competition decreases financial stability; as are studies that use either OLS or GMM.

Table 4.9

Results for Frequentist Methods

Response variable	OLS			Fixed effects		
Competition effect	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-0.4588	1.9175	0.811	-4.8242	5.0451	0.346
Samplesize	-0.0014	0.0252	0.956	-0.1182	0.0948	0.221
T	-0.0433	0.0251	0.084	-0.0233	0.0247	0.352
Sampleyear	0.0005	0.0038	0.892	-0.0092	0.0052	0.084
Countries examined						
Developed	-0.0257	0.0421	0.542	0.0254	0.0226	0.269
Developing and transition	-0.0161	0.0421	0.701	-0.0047	0.0123	0.702
Design of the analysis						
Quadratic	0.0124	0.0649	0.848	0.1231	0.1533	0.427
Endogeneity	-0.0003	0.0337	0.993	0.0735	0.0282	0.013
Macro	-0.0520	0.0398	0.192	omitted		
Averaged	0.0210	0.0305	0.490	0.0023	0.0250	0.926
Treatment of stability						
Dummies	0.0383	0.0605	0.527	-0.0514	0.0337	0.137
NPL	0.0084	0.0466	0.857	-0.0001	0.0479	0.999
Z_score	-0.0297	0.0281	0.290	-0.0488	0.0321	0.138
Profit volatility	0.0202	0.0328	0.538	-0.0540	0.0330	0.111
Profitability	-0.0769	0.0249	0.002	-0.0743	0.0221	0.002
Capitalization	-0.0554	0.0463	0.232	-0.1235	0.0313	0.000
DtoD	-0.0917	0.0338	0.007	-0.1018	0.0142	0.000
Treatment of competition						
H-statistic	0.0976	0.0889	0.272	-0.0481	0.1090	0.662
Boone	-0.0842	0.0736	0.253	-0.0951	0.0869	0.281
Concentration	0.1321	0.0440	0.003	0.0505	0.0324	0.129
Lerner	0.0279	0.0410	0.496	-0.0411	0.0375	0.281
HHI	0.0942	0.0540	0.081	0.0994	0.0552	0.080

Response variable	OLS			Fixed effects		
Competition effect	**Coeff**	**SE**	**p-value**	**Coeff**	**SE**	**p-value**
Estimation method						
Logit	-0.1082	0.0657	0.099	0.0010	0.0194	0.960
OLS	-0.1758	0.0619	0.004	-0.0891	0.0303	0.006
FE	-0.0730	0.0414	0.078	-0.0510	0.0274	0.071
RE	-0.0707	0.0507	0.163	-0.0593	0.0427	0.175
GMM	-0.0513	0.0327	0.117	-0.1429	0.0441	0.003
TSLS	-0.0513	0.0462	0.267	-0.0207	0.0275	0.457
Control variables						
Regulation	-0.0532	0.0334	0.111	0.0238	0.0160	0.146
Ownership	-0.0134	0.0506	0.792	-0.0084	0.0102	0.419
Global	0.0657	0.0327	0.045	-0.0581	0.0339	0.096
Publication characteristics						
Citations	0.1037	0.0273	0.000	omitted		
Firstpub	0.0175	0.0058	0.002	omitted		
IFrecursive	0.0763	0.1295	0.556	omitted		
Reviewed journal	-0.1475	0.0433	0.001	omitted		
Constant	-0.0249	0.2531	0.922	1.2322	0.8916	0.176
Studies			35			35
Observations			762			762

Note. The OLS and fixed effects estimation includes all the explanatory variables in the equation. The inverse number of estimates per study is taken as the weight. The standard errors are clustered at the study level.

4.8.4 Specifications weighted by inverse variance

The final robustness check introduces a different weighting specification. The baseline estimation model uses a weighting method that weights by the inverse of the number of estimates per study. Table 4.10 weights variables by the inverse variance of the respective PCC estimates for the subsequent BMA and OLS estimation. This produces some differences in the estimated coefficient values and the statistical significance of the variables.

Note that weighting by the inverse variance of the PCC estimate means that the constant term represents the SEPCC coefficient in the transformed equation. As a result, it is included in every model evaluated in the BMA analysis. This is evidenced in Table 4.10 by the fact that SEPCC has a PIP of 1.0000, and its corresponding posterior standard deviation (Post. SD) is reported as "NA". However, in the corresponding OLS estimation, while the estimated coefficient for SEPCC is relatively large, it is statistically insignificant at the 5 percent level. This again supports the conclusion of no publication bias in the literature.

It is noteworthy that other variables can have a high PIP value but be insignificant in the corresponding OLS estimation. For example, the recursive impact factor (IFrecursive) has a PIP of 0.6314, but its estimated coefficient in the OLS estimation is very small (-0.0227), with a p-value of 0.777. Of particular interest in Table 4.10 are the results for Quadratic. This variable, which identifies estimates where the original study specified a nonlinear (quadratic) relationship for competition and financial stability, has a PIP equal to 1.0000 in the BMA analysis. The corresponding OLS estimate of the coefficient is 0.2106, suggesting that quadratic specifications of the competition-stability relationship generally produce results that are more favourable to the hypothesis that competition contributes positively to stability.

Table 4.10

Results for Specifications Weighted by Inverse Variance of the Estimates

Response variable	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Data characteristics						
SEPCC	-2.3230	NA	1.0000	-3.7988	2.9350	0.196
Samplesize	-0.0002	0.0014	0.0882	-0.0121	0.0203	0.553
T	0.0014	0.0038	0.1892	0.0154	0.0107	0.151
Sampleyear	0.0101	0.0013	1.0000	0.0137	0.0027	0.000
Countries examined						
Developed	-0.0204	0.0277	0.3997	-0.0398	0.0315	0.208
Developing and transition	0.0016	0.0078	0.0596	0.0131	0.0244	0.593
Design of the analysis						
Quadratic	0.2486	0.0282	1.0000	0.2106	0.0454	0.000
Endogeneity	0.0049	0.0093	0.2706	0.0093	0.0173	0.590
Macro	0.0006	0.0052	0.0300	0.0142	0.0371	0.702
Averaged	-0.0003	0.0087	0.0177	0.0132	0.0216	0.542
Treatment of stability						
Dummies	0.0000	0.0020	0.0340	-0.0156	0.0199	0.431
NPL	0.0013	0.0044	0.1031	0.0134	0.0145	0.358
Z_score	0.0000	0.0008	0.0211	0.0050	0.0123	0.684
Profit volatility	0.0000	0.0010	0.0172	0.0065	0.0123	0.599
Profitability	-0.0001	0.0014	0.0251	-0.0017	0.0154	0.912
Capitalization	-0.0007	0.0041	0.0465	-0.0227	0.0228	0.320
DtoD	-0.0963	0.0741	0.7021	-0.1106	0.0250	0.000
Treatment of competition						
H-statistic	0.0046	0.0146	0.1199	0.0103	0.0352	0.769
Boone	0.0009	0.0041	0.0714	0.0041	0.0087	0.633
Concentration	0.0002	0.0019	0.0238	-0.0000	0.0114	0.999
Lerner	-0.0035	0.0068	0.2589	-0.0144	0.0100	0.152
HHI	-0.0001	0.0013	0.0293	-0.0065	0.0086	0.449

Response variable	Bayesian model averaging			OLS		
Competition effect	**Post. mean**	**Post. SD**	**PIP**	**Coeff**	**SE**	**p-value**
Estimation method						
Logit	0.0008	0.0037	0.0697	0.0029	0.0057	0.613
OLS	-0.0061	0.0119	0.2499	-0.0405	0.0186	0.029
FE	-0.0032	0.0073	0.2028	-0.0356	0.0185	0.055
RE	-0.0558	0.0154	0.9965	-0.0725	0.0292	0.013
GMM	-0.0683	0.0158	0.9981	-0.0806	0.0392	0.040
TSLS	0.0001	0.0014	0.0220	-0.0100	0.0071	0.161
Control variables						
Regulation	0.0001	0.0021	0.0217	0.0026	0.0170	0.877
Ownership	-0.0038	0.0107	0.1453	-0.0093	0.0228	0.684
Global	-0.0001	0.0014	0.0255	-0.0088	0.0109	0.416
Publication characteristics						
Citations	-0.0267	0.0179	0.7452	-0.0259	0.0128	0.043
Firstpub	0.0024	0.0028	0.5407	0.0053	0.0035	0.127
IFrecursive	-0.0931	0.0749	0.6314	-0.0227	0.0802	0.777
Reviewed journal	-0.0378	0.0490	0.4042	-0.1007	0.0473	0.033
Constant	0.0012	0.0092	0.0810	0.1084	0.1951	0.578
Studies			35			35
Observations			762			762

Note. The table presents results of BMA and OLS estimation. Post. Mean is posterior mean, Post. SD is posterior standard deviation and PIP is posterior inclusion probability. The standard errors are clustered at the study level.

4.9 Estimate the Results for Linear Coefficients

This section re-analyses the data by considering only those estimates that use a linear specification for the competition variable in the original study. It excludes all non-linear competition coefficients. It does that because the previous analysis ignored the covariance of the two estimated coefficients when calculating the standard error of the competition effect. It is not clear how much this changes the results. Given the substantial impact for Quadratic identified in the previous section, this becomes a topic of interest. Of the 716 linear coefficient estimates available, 318 are from developed countries, 156 are from developing and transition countries, with the remaining 242 coming from the mixed country category. The subsequent analysis focuses on the estimates of mean PCC and the identification of publication bias via the FAT.

Table 4.11 reports the estimates of mean PCC for the three country groups. For all sub groups the estimated competition coefficient is statistically insignificant and the effect size is small (< 0.07).

Table 4.11

Estimates of the Competition Effect for Different Country Groups

Country group	**Unweighted**			**Weighted**			**No of estimates**
	Mean	**95% CI**		**Mean**	**95% CI**		
All	-0.0122	-0.0323	0.0079	-0.0157	-0.0430	0.0116	716
Developed	-0.0027	-0.0338	0.0283	0.0008	-0.0356	0.0371	318
Developing and transition	-0.0161	-0.0505	0.0183	-0.0319	-0.1059	0.0422	156

Note. The table presents the mean PCC of competition coefficient estimates for all estimates, estimates from developed (OECD) countries, and developing and transition (non-OECD) countries. The left side of the table presents, unweighted mean values and 95% confidence interval. In the right side of the table, estimates are weighted by inverse number of estimates per study.

Table 4.12 follows the same procedure as Table 4.2 and reports FAT results for the sample of linear estimates using weighted (panel A) and unweighted regressions (panel B). The results of Table 4.12 are statistically insignificant everywhere and confirm the baseline finding of no publication bias.

Table 4.12

Funnel Asymmetry Tests

Panel A				
Unweighted Regressions	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
SE (Publication bias)	-0.0747	-0.6393	-0.1178	-0.3178
Constant (effect beyond bias)	-0.0101	0.0100	-0.0089	0.0006
No of estimates	716	560	716	560
No of studies	31	24	31	24
Panel B				
Weighted Regressions	**FE**	**FE_Published**		
SE (Publication bias)	1.1511	-0.7584		
Constant (effect beyond bias)	-0.0525	0.0058		
No of estimates	716	560		
No of studies	31	24		

Note. The table presents the results of FAT. Panel A presents unweighted regressions and panel B presents weighted regressions. The standard errors are clustered at the study level. Fixed effects estimation uses study dummies and instrumental variable estimation uses the logarithm of the number of observations as the instrumental variable.

Table 4.13 repeats the analysis, this time correcting for heteroscedasticity, as in Table 4.3. Consistent with previous results, the associated FAT parameters (Constant – publication bias) are statistically insignificant, once again producing no evidence of publication bias. Further, the bias-corrected estimates of mean PCC (1/SE – effect beyond bias) are small, less than 0.07. Overall, Tables 4.12 and 4.13 produce results similar to Tables 4.2 and 4.3. It confirms that previous results were not driven by the inclusion of estimates derived from non-linear specifications of the competition effect.

Table 4.13

Heteroscedasticity-Corrected Funnel Asymmetry Tests

Panel A				
Weighted by precision	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
1/SE (effect beyond bias)	-0.0062	-0.0025	-0.0122	-0.0069
Constant (publication bias)	0.1590	-0.2344	0.6330	0.0556
No of estimates	716	560	716	560
No of studies	31	24	31	24
Panel B				
Weighted by precision and No. of observations	**FE**	**FE_Published**		
1/SE (effect beyond bias)	-0.0037	0.0016		
Constant (publication bias)	-0.2196	-0.5713		
No of estimates	716	560		
No of studies	31	24		

Note. The table presents the results of Heteroscedasticity-corrected FAT. Panel A presents weighted regressions by precision and panel B presents weighted regressions by precision and number of observations. The standard errors are clustered at the study level. Fixed effects estimation uses study dummies and instrumental variable estimation uses the logarithm of the number of observations as the instrumental variable.

4.10 Removal of Concentration Measures

Some researchers have argued that concentration ratio and HHI are not pure measures of competition (Claessens & Laeven, 2004; Schaeck et al., 2009). This section follows up that concern by investigating the consequences of excluding estimates that use these measures. Tables 4.14, 4.15, and 4.16 repeat the immediately preceding analyses of mean PCC, FAT, and heteroscedasticity-corrected FAT, except this time they exclude all competition effects that are based on concentration ratio and HHI. This leaves a total of 470 estimates. 243 estimates are associated with developed countries, 120 with developing and transition countries, and 107 with a mix of country types.

Table 4.14 reports the first set of results for mean PCC. Of the 6 estimates of mean PCC, only one -- for developed countries and using the weighted method of estimation – is statistically significant. All are economically small, with effect sizes less than 0.07. This is consistent with previous conclusions that the relationship between competition and financial stability is weak at best.

Table 4.14

Estimates of the Competition Effect for Different Country Groups

Country group	**Unweighted**			**Weighted**			**No of estimates**
	Mean	**95% CI**		**Mean**	**95% CI**		
All	-0.0168*	-0.0366	0.0031	-0.0378*	-0.0805	0.0049	470
Developed	-0.0249*	-0.0498	0.0001	-0.0334**	-0.0595	-0.0073	243
Developing and transition	-0.0085	-0.0537	0.0368	-0.0594	-0.1653	0.0465	120

Note. The table presents the mean PCCs of competition coefficient estimates for all estimates, estimates from developed (OECD) countries, and developing and transition (non-OECD) countries. The left side of the table presents, unweighted mean values and 95% confidence interval. In the right side of the table, estimates are weighted by inverse number of estimates per study. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Tables 4.15 and 4.16 report the FAT and heteroscedasticity-corrected FAT results after excluding competition estimates using concentration ratio and HHI. Across both tables, the associated FAT coefficients are everywhere statistically insignificant. There is once again no evidence of publication bias.

Table 4.15

Funnel Asymmetry Tests

		Panel A		
Unweighted Regressions	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
SE (Publication bias)	-2.6876	-2.6905	-1.1234	-0.8654
Constant (effect beyond bias)	0.0495	0.0562	0.0109	0.0064
No of estimates	470	375	470	375
No of studies	27	22	27	22
		Panel B		
Weighted Regressions	**FE**	**FE_Published**		
SE (Publication bias)	-2.6611	-2.6816		
Constant (effect beyond bias)	0.0460	0.0457		
No of estimates	470	375		
No of studies	27	22		

Note. The table presents the results of FAT. Panel A presents unweighted regressions and panel B presents weighted regressions. The standard errors are clustered at the study level. Fixed effects estimation uses study dummies and instrumental variable estimation uses the logarithm of the number of observations as the instrumental variable.

Table 4.16

Heteroscedasticity-Corrected Funnel Asymmetry Tests

Panel A				
Weighted by precision	**FE**	**FE_Published**	**Instrument**	**Instrument_Published**
1/SE (effect beyond bias)	0.0104	0.0332	-0.0002	-0.0001
Constant (publication bias)	-1.1507	-2.8162	-0.1576	-0.3882
No of estimates	470	375	470	375
No of studies	27	22	27	22
Panel B				
Weighted by precision and No. of observations	**FE**	**FE_Published**		
1/SE (effect beyond bias)	0.0370	0.0766		
Constant (publication bias)	-2.9271	-4.9265		
No of estimates	470	375		
No of studies	27	22		

Note. The table presents the results of Heteroscedasticity-corrected FAT. Panel A presents weighted regressions by precision and panel B presents weighted regressions by precision and number of observations. The standard errors are clustered at the study level. Fixed effects estimation uses study dummies and instrumental variable estimation uses the logarithm of the number of observations as the instrumental variable.

4.11 Conclusion

Much research has attempted to determine the relationship between bank competition and financial stability, no doubt stimulated by policymakers' desire to avoid a recurrence of the global financial crisis. Despite a plethora of studies, there is no consensus about the nature of this relationship. This chapter performs a MRA on bank competition and financial stability from recent literature. A total of 762 estimates are extracted from 35 studies. A variety of variable specifications, sample selection, and estimation procedures are employed. The generally consistent finding across all of these is that the relationship between competition and financial stability, if it exists at all, is small and economically unimportant. Further, the literature appears to present a representative picture of this relationship, with no evidence of publication bias.

A closer examination of the respective competition effects reveals that there is substantial heterogeneity across estimates. This chapter uses BMA to identify factors that systematically influence the estimated relationship between competition and financial stability. It finds that country coverage, the type of measures used for stability and competition, the type of estimation methods employed, and measures of publication quality are all important determinants of the estimated competition-stability relationship.

Chapter Five

5.1 Introduction

The relationship between competition and financial stability is highly contested in the banking literature. The previous chapters on meta-regression-analysis of bank competition and financial stability present reasons for the heterogeneity in the literature. The selected sample of countries, sample period, type of measure used to assess the degree of competition and stability, and type of estimation methods are all associated with different estimates for the relationship of competition and stability. This chapter brings new data to bear on the subject. It uses bank-level data in the USA for the period between 2000 and 2017.

The results of Zigraiova and Havranek (2016) indicate that the effect of competition on stability is larger in developed countries (though even there they conclude that the effect is not very large). Accordingly, bank level data from the USA would seem to be a good place to find a significant competition effect if it exists. Z&H report that there are systematic differences in estimated competition effects depending on the type of measure used for competition and stability. This chapter uses three measures of bank competition: H-statistic, the Lerner index and the Boone indicator. Bank-level stability is also measured using three different variables: Z-score, non-performing loans, and distance-to-default. In addition, logistic R-squared and the change in conditional value at risk (CoVaR) are used to measure systemic stability.

Zigraiova and Havranek (2016) find that the selected sample of countries, sample period, proxy measures of competition and stability, and estimation method are the main reasons for the conflicting evidence in the literature. The findings of the chapter empirically confirm their conclusions. The effect of competition on stability varies with the empirical measure of competition and stability. When the measure of stability is Z-score, all the competition measures are negatively associated with stability. A similar relationship is observed when the measure of stability is distance-to-default, though the associated estimates are not statistically significant. However, different results obtain when non-performing loans (NPL) are used to measure bank-level stability. In that case, the Lerner index and the Boone indicator are estimated to be positively associated with stability. Nevertheless, even when the competition measures are statistically significant, the economic effects of competition on financial stability implied by the respective estimates are negligible.

This chapter performs several robustness checks. The results change little when the sample excludes the global financial crisis. Further, while other studies report that bank concentration affects the estimated relationship between competition and stability, little evidence of that is found here. Finally, when the relationship between competition and systemic stability is estimated, all the competition variables are found to be statistically insignificant.

The remainder of the chapter is organized into ten sections. Section 5.2 presents a review of related literature. Section 5.3 explains the different competition measures and section 5.4 describes the different stability measures used in this study. Sections 5.5 and 5.6 discuss the estimation method and data, respectively. The results are reported in section 5.7. A variety of robustness tests are performed in section 5.8. Section 5.9 discusses systemic stability and section 5.10 summarizes the results and concludes.

5.2 Literature Review

5.2.1 Competition-fragility hypothesis

Until the late 1960s, the banking sector in the USA was protected by state laws with the aim of limiting branches, multi-bank holdings, and interstate expansions. These laws were liberalized in the 1970s and 1980s and reduced barriers to entry, encouraging competition in the banking sector. In addition, technological changes and developments in the money market also contributed to a rise in competition (Vives, 2001).

Keeley (1990) explains that when there is a competition in the banking sector, it reduces the incentive to undertake prudent banking businesses and increases the risk of bank failures. Apart from competition, a decline in the capital to assets ratio is another reason for bank failures. Keeley (1990) describes two reasons for the decline in capital to asset ratio. Firstly, when the asset risk is constant, holding a lower capital level increases the risk of bank failure. Secondly, as explained by Furlong and Keeley (1989), low capital requirements imposed by the regulatory authorities create an incentive for banks to increase asset risk. If banks hold high amounts of capital they can internalize the risk of their business activities (Hellmann et al., 2000). The relaxation of capital regulations during liberalization has indirectly supported risk taking. Allen and Gale (2004); Keeley (1990); Marcus (1984) find that increases in competition reduce the charter value of a bank and hence increase the risk of bank failure. This has led to the “competition-fragility” hypothesis.

Many empirical studies find evidence to support the competition-fragility hypothesis (Agoraki et al., 2011; Beck et al., 2013; Berger et al., 2009; Fernandez & Garza-Garciab, 2012; Fu et al., 2014; Tabak, Fazio, & Cajueiro, 2012; Yeyati & Micco, 2007). These studies present their results based on various measures of stability and competition. A full discussion of the different measures of competition and stability is done in Sections 5.3 and 5.4. For example, Tabak et al. (2012) use the Boone indicator as the competition measure . Other studies use the Lerner index as the competition measure (Agoraki et al., 2011; Beck et al., 2013; Berger et al., 2009; Fernandez & Garza-Garciab, 2012; Fu et al., 2014). Yeyati and Micco (2007) present their evidence using the H-statistic as a measure of competition.

5.2.2 Competition-stability hypothesis

Boyd and De Nicolo (2005) revisit Keeley's view and introduce an opposing theoretical explanation known as the competition-stability hypothesis. According to their view, banks compete in both deposits and lending markets. In a less competitive market, banks pay low deposit rates and charge high interest from borrowers. That allows them to make more profits. At the same time, high loan rates increase the cost of borrowing and decrease the profit margin of borrowers. This raises the probability to default the loan repayment, which in turn increases the non-performing loan ratio/credit risk of banks.

Boyd and De Nicolo (2005) explain that in a competitive banking system, banks offer lower borrowing rates to their clients and this works to reduce the level of credit risk. As a result, they promote the argument that competition in the banking system contributes to financial stability. Caminal and Matutes (2002) take a different tack to this issue and argue that monopolists accept more risk and have a greater tendency go bankrupt compared to competitive banks. Increasing competition reduces the power of individual players, and this reduces the risk of bank failure.

Proponents of the competition-stability hypothesis also use a variety of measures to assess the degree of competition and stability in their empirical analyses (Amidu & Wolfe, 2013; Goetz, 2016; Jeon & Lim, 2013; Liu, Molyneux, & Wilson, 2013; Schaeck & Cihak, 2008, 2014; Schaeck et al., 2009). The estimation results of Schaeck et al. (2009) are based on the H-statistic and a dummy variable to represent the occurrence of a systemic crisis.

Results indicate that there is a positive relationship between competition and stability. They explain that time to crisis increases with an increase in competition. Schaeck and Cihak (2008, 2014) assess the relationship between the Boone indicator and Z-score. Their analysis supports the view that competitive banks are efficient and stable. Amidu and Wolfe (2013) use both the Lerner index and H-statistic as competition measures; and Z-score, NPL, bank profitability as stability measures. They find that more competition is associated with greater stability.

5.2.3 Bank level competition and financial stability: empirical findings

Zigraiova and Havranek (2016) report that empirical studies focused on individual countries do not find strong evidence for either the competition-fragility hypothesis or the competition-stability hypothesis. Heterogeneity of bank-level studies leads to inconclusive evidence.

Fungáčová and Weill (2013) analyse the impact of bank competition on the financial stability of Russian banks for the time period 2001 to 2007. They find support for the competition-fragility hypothesis. Jiang et al. (2017) examine the relationship between regulation-induced competition and market risk of US bank-holding companies. They find that competition increases bank risk. Fernandez and Garza-Garciab (2012) examine the Mexican banking sector. Their evidence supports the competition-stability view. Liu and Wilson (2013) find that the relationship between competition and stability varies based on the different types of Japanese banks. For regional-level banks, increased competition appears to increase risk level. On the contrary, for national banks, increased competition reduces risk level. Similarly, Jeon and Lim (2013) also find that the relationship between competition and stability in Korea varies based on the type of bank.

5.3 Competition Measures

There is no consensus regarding the best measure to capture the competition effect. This section presents evidence for the use of various measures of competition in empirical studies. In the early 1990s, empirical researchers used structural measures of competition. Structural measures are based on the structure-conduct-performance hypothesis (Berger et al., 2004). Structural measures assume that greater concentration represents decreased competition.

Two historical measures of bank competition are the bank concentration ratio and Herfindahl-Hirschman index (HHI). The bank concentration ratio is defined as total assets of the three or five largest banks as a percentage of total assets of the entire banking system. HHI is the sum of the squared market share of each bank (Bikker & Haaf, 2002b). However, the empirical literature has come to the conclusion that these are not good measures for bank competition (Claessens & Laeven, 2004; Schaeck et al., 2009). As explained by Leon (2014) "the new empirical industrial organization" proposes that competition can be directly estimated using the conduct of firms in the market. These, non-structural measures of competition focus on input costs and output prices of firms. The prominent non-structural measures of competition are H-statistic, the Lerner index, and the Boone indicator. These measures capture different characteristics of the banking system (Leon, 2015). Therefore, this study focuses on these three measures of competition.

5.3.1 H-statistic

Panzar and Rosse (1987) H-statistic assesses the competitiveness of the market based on revenue and costs. It is the sum of the elasticities of a bank's total revenue with respect to its input prices. It is negative for a monopolist, equal to 1 for a competitive price-taking firm and varies from 0 to 1 for monopolistic competition. The H-statistic assesses the ability of a bank to pass on increases in factor input prices to customers. As explained by Bikker and Haaf (2002a), under monopoly, an increase in input prices leads to an increase in marginal costs, which reduces equilibrium output, and consequently reduces the revenue of the monopolistic firm. This gives a value of the H-statistic less than 0 for a monopolistic firm. In a perfectly competitive situation, H-statistic = 1. A firm's output level remains constant and the increase in firm's price is proportionate to the increase in both average and marginal cost. Under monopolistic competition, H-statistic is 0 < and < 1. Banks produce more output and price is less than the optimal condition. Revenue of the individual firm depends on the degree of product differentiation among the rival firms within the industry.

Claessens and Laeven (2004) empirically estimate the H-statistic using the following method;

$$\ln (P_{it}) = \alpha_i + \beta_{1i}\, ln(W_{1,it}) + \beta_{2i}\, ln(W_{2,it}) + \beta_{3i} ln(W_{3,it}) + \gamma_{1i}\, ln(Y_{1,it}) + \gamma_{2i}\, ln(Y_{2,it}) + \gamma_{3i}\, ln(Y_{3,it}) + \varepsilon_{it} \quad , \tag{5.1}$$

where P_{it} is the ratio of interest revenue to total assets (a proxy for output price), W_1 is the ratio of interest expenses to total deposits and money market funding (a proxy for the input price of deposits), W_2 is the ratio of personnel expense to total assets (a proxy for the price of labour), and W_3 is the ratio of other operating and administrative expenses to total assets (a proxy for price of fixed capital), with *i* denoting bank *i* and *t* denoting time *t*. Y_1 is a control variable for the ratio of equity to total assets, Y_2 controls for the ratio of net loans to total assets, and Y_3 is the log of total assets to capture size effects. All variables enter the equation in natural logarithms. The H-statistic for firm *i* is calculated as $\beta_{1i} + \beta_{2i} + \beta_{3i}$. Equation (5.1) is estimated using OLS with time dummies, and alternatively with GLS and time dummies. An alternative dependent variable is also used to estimate H-statistic, as shown in equation (5.2).

$$\ln (R_{it}) = \alpha_i + \beta_{1i}\, ln(W_{1,it}) + \beta_{2i}\, ln(W_{2,it}) + \beta_{3i} ln(W_{3,it}) + \gamma_{1i}\, ln(Y_{1,it}) + \gamma_{2i}\, ln(Y_{2,it}) + \gamma_{3i}\, ln(Y_{3,it}) + \varepsilon_{it}$$

(5.2)

where R_{it} is the ratio of total revenue to total assets (a proxy for output price), and the remaining variables are defined as above. Equation (5.2) is also estimated using OLS with time dummies, and GLS with time dummies. The overall H-statistic is an average calculated from these four estimation models.

The interpretation of the H-statistic is only valid if the country is in long-run equilibrium. The long-run equilibrium condition is determined from equation (5.3) using the E-statistic = $\beta_{1i} + \beta_{2i} + \beta_{3i}$.

$$\ln (ROA_{it}) = \alpha_i + \beta_{1i}\, ln(W_{1,it}) + \beta_{2i}\, ln(W_{2,it}) + \beta_{3i} ln(W_{3,it}) + \gamma_{1i}\, ln(Y_{1,it}) + \gamma_{2i}\, ln(Y_{2,it}) + \gamma_{3i}\, ln(Y_{3,it}) + \varepsilon_{it} \qquad (5.3)$$

In long-run equilibrium position, returns on bank assets should be unrelated to input prices (Claessens & Laeven, 2004; Goddard & Wilson, 2009; Schaeck et al., 2009). Accordingly, a test for long-run equilibrium is given by H_0: E-statistic = 0. When this hypothesis is rejected, the market is concluded to not be in long-run equilibrium.

The estimation of the H-statistic is based purely on bank-level information. No market-based information is required to compute it. This is an advantage of the H-statistic (Leon, 2014). The pitfalls of the H-statistic are that it can be positive for a monopoly and negative for a competitive firm in the short term, or for a firm with constant average costs (Bikker et al., 2012). Goddard and Wilson (2009) explain that the static equilibrium condition of Panzar and Rosse (1987) H-statistic is not practical because there are many situations where markets will be out of long-run equilibrium.

5.3.2 The Lerner index

The Lerner index captures the market power of a bank. It compares the bank's output price with its associated marginal costs. The marginal cost of a bank is estimated from a translog cost function (Spierdijk & Zaouras, 2016). This chapter follows the methodology of Anginer et al. (2014); Demirguc-Kunt and Martinez-Peria (2010) to estimate the marginal cost of each bank. Price and marginal cost are equal in perfect competition, but diverge in less competitive conditions. A larger value indicates a wider gap between output price and marginal costs and, thus, greater monopoly power (Leon, 2014). The marginal cost of each bank is estimated by using equations (5.4) – (5.6), and then the Lerner index is computed from equation (5.7).

$$
\begin{aligned}
\ln(C_{it}) = {} & \alpha_i + \beta_{1i}\, ln(Q_{it}) + \beta_{2i}\,(ln(Q_{2,it}))^2 + \beta_{3i}\, ln(W_{1,it}) + \beta_{4i}\, ln(W_{2,it}) \\
& + \beta_{5i} ln(W_{3,it}) + \beta_{6i}\, ln(Q_{it}) * ln(W_{1,it}) + \beta_{7i}\, ln(Q_{it}) * ln(W_{2,it}) \\
& + \beta_{8i}\, ln(Q_{it}) * ln(W_{3,it}) + \beta_{9i}\,(ln(W_{1,it}))^2 + \beta_{10i}\,(ln(W_{2,it}))^2 \\
& + \beta_{11i}\,(ln(W_{3,it}))^2 + \beta_{12i}\, ln(W_{1,it}) * ln(W_{2,it}) + \beta_{13i}\, ln(W_{1,it}) * ln(W_{3,it}) \\
& + \beta_{14i}\, ln(W_{2,it}) * ln(W_{3,it}) + \theta_i D + \varepsilon_{it}
\end{aligned}
\tag{5.4}
$$

where C_{it} is the sum of total costs, Q_{it} is the quantity of total assets in million dollars, $W_{1,it}$ is the ratio of interest expenses to total assets, $W_{2,it}$ is personnel expenses as a percentage of total assets, and $W_{3,it}$ is administrative and other operating expenses as a percentage of total assets. D indicates time dummies. The subscripts i and t denote bank and quarter, respectively. All variables in equation (5.4) are specified in natural logarithms. Estimation uses ordinary least squares with five restrictions imposed on the regression coefficients as shown in equation (5.5).

$\beta_{3\mathrm{i}} + \beta_{4\mathrm{i}} + \beta_{5\mathrm{i}} = 1;$

$\beta_{6\mathrm{i}} + \beta_{7\mathrm{i}} + \beta_{8\mathrm{i}} = 0;$

$\beta_{9\mathrm{i}} + \beta_{12\mathrm{i}} + \beta_{13\mathrm{i}} = 0;$

$\beta_{10\mathrm{i}} + \beta_{12\mathrm{i}} + \beta_{14\mathrm{i}} = 0$; and

$$\beta_{11\mathrm{i}} + \beta_{13\mathrm{i}} + \beta_{14\mathrm{i}} = 0 \qquad (5.5)$$

The Lerner index is calculated using equations (5.6) and (5.7) below. In equation (5.6) and (5.7), MC_{it} is marginal cost, and P_{it} is the ratio of total revenue to total assets. The subscripts i and t denote bank and quarter, respectively.

$$MC_{it} = \frac{\partial C_{it}}{\partial Q_{it}}$$

$$= \frac{C_{it}}{Q_{it}} \left[\beta_{1i} + 2\beta_{2i} lnQ_{it} + \beta_{6i} \ln\left(W_{1,it}\right) + \beta_{7i} \ln\left(W_{2,it}\right) + \beta_{8i} \ln\left(W_{3,it}\right)\right] \qquad (5.6)$$

$$Lerner_{it} = (P_{it} - MC_{it})/P_{it} \ , \qquad (5.7)$$

The Lerner index is a flexible measure. It measures market power for individual banks. More importantly, it can be calculated with a limited number of observations, which is particularly important given limited data availability. Unlike the H-statistic, the Lerner index does not require a banking system to be in the long-run equilibrium.

On the other hand, it does have some drawbacks. It is a static measure based on the price of the bank for a given time period. Further, some would argue that pricing power is not a good proxy for competition (Leon, 2014, 2015). Also, Spierdijk and Zaouras (2016) argue that the Lerner index is one-dimensional, and that maximum revenue is subject to a minimum profit constraint. Oliver, Fumás, and Saurina (2006) point out that market power differs across loan products and an overall Lerner index does not capture real market power.

5.3.3 The Boone indicator

Boone (2008) introduces a new non-structural measure of competition. This measure considers the impact of efficiency on performance. According to Boone (2008), competition tor is defined by two key characteristics. Firstly, firms produce close substitutes and secondly, there are low barriers to entry.

When there is an increase in product substitution, consumers will obtain products and services from the firms that charge the least. This leads to a negative relationship between profits and costs. Boone (2008) argues that this effect will be stronger for firms in competitive markets. Equation (5.8) shows the estimation of the Boone indicator (β).

$$\ln(\pi_{it}) = \alpha + \beta_i ln(C_{it}) , \quad (5.8)$$

where π_{it} indicates return on assets of bank *i* at time *t*, and C is the cost. β_i is referred to as the Boone indicator.

As noted, profits are expected to be higher for banks with lower marginal costs ($\beta_i < 0$). The inverse relationship between marginal costs and profits should be stronger for banks in more competitive environments. As a result, banks in more competitive markets should have β values that are more negative than banks in less competitive markets.

Schaeck and Cihak (2014) use an average cost to estimate the Boone indicator. Tabak et al. (2012); van Leuvensteijn, Bikker, van Rixtel, and Sørensen (2011) use marginal cost to estimate the Boone indicator. This chapter uses both the average cost and marginal cost. This allows to observe the estimation difference based on the average cost and the marginal cost.

Marginal cost is calculated from the estimated translog function in equation (5.4). Equations (5.9) and (5.10) estimate the competitive condition (β) of each bank for the full sample period.

$$\ln(ROA_{it}) = \alpha_i + \beta_i ln(AC_{it}) + D_{it} + \varepsilon_{it} , \tag{5.9}$$

$$\ln(ROA_{it}) = \alpha_i + \beta_i ln(MC_{it}) + D_{it} + \varepsilon_{it} , \tag{5.10}$$

where ROA_{it} indicates return on assets of bank *i* at time *t*, AC is average cost, MC is marginal cost, and β is the Boone indicator. Time dummies are included to control for the timely changes in the US banking system.

The main advantage of the Boone indicator is that it estimates the relationship between costs and profits in a continuous market. It only requires information about profits (or market shares) and costs, and it is a non-price measure. Both the Lerner index and the H-statistic require static price when estimating competition. But the Boone indicator has its limitations. The model used to calculate the Boone indicator assumes that efficiency is one dimensional, ignoring other aspects. Banks may convert their efficiency gains into future investments. In that case, the efficiency gains of banks from competition do not show up in lower costs and/or higher profits in the short term (Leon, 2015).

5.4 Stability Measures

This chapter considers both accounting-based and market-based measures of stability. Accounting-based measures are computed using historical accounting data. Market-based measures use stock market data to calculate stability measures. Market-based measures are more forward-looking compared to accounting-based measures.

5.4.1 Accounting-based measures

Z-score is a widely used, accounting-based risk measure and it is computed using individual, bank-level data. It compares the capital buffer and returns of the bank with the volatility of returns, and interprets it as the inverse probability of default (Boyd et al., 1993;

Boyd & Runkle, 1993). A higher Z-score indicates a lower probability of default and hence more stability. It is estimated as follows;

$$Z - score_{\ it} = \frac{ROA_{it} + \frac{Equity_{it}}{Assets_{it}}}{SDROA_{it}}, \tag{5.11}$$

where ROA_{it} indicates the return on assets of the bank *i* at time *t*, $Equity_{it}$ is the total equity of the bank *i* at time *t*, $Assets_{it}$ is the total assets of the bank *i* at time *t* , and $SDROA_{it}$ is the standard deviation of ROA, or the volatility of returns.

Lepetit and Strobel (2013) explain different approach to calculating time-varying Z-scores. They recommend computing time-varying standard deviation rather than one standard deviation for the full sample period. The most common approach is a twelve-quarter rolling time window to calculate the standard deviation of ROA (Beck et al., 2013; Boyd et al., 2006; Leroy & Lucotte, 2017). This approach is the most preferred approach for unbalanced panel data. It avoids using different lengths of time period for different banks when computing the denominator of the equation. This chapter follows the same approach and use a twelve-quarter rolling time window.

The ratio of non-performing loans to total loans is another accounting-based measure for measuring the credit risk of the bank. The higher percentage of NPLs indicates an increase in credit risk and less stability (Berger et al., 2009; Jiménez, Lopez, & Saurina, 2013; S. Kasman & A. Kasman, 2015).

The accounting-based measures are easy to calculate and can be used for any banking system. However, they only consider the stability of individual banks. They ignore the spillover risk that a defaulting bank may cause other interconnected financial institutions. Furthermore, if a bank is able to manipulate its accounting information, these measures will misrepresent its financial stability (The World Bank, 2016).

5.4.2 Market-based measures

The Merton (1974) distance-to-default measure is a market-based measure that estimates the insolvency risk of a bank. The measure consists of an estimate of the probability of default for each bank at any given point in time. It takes the difference between the current market value of bank assets and the face value of its debt, and divides by the volatility of its assets (Bharath & Shumway, 2008). A higher value results either from an increase in the bank's assets and/or a decrease in the volatility of its assets (Kliestik, Misankova, & Kocisova, 2015). As such, it indicates a lower probability of default, and thus greater stability.

Distance-to-default is interpreted as the market's perception about the bank's stability in the future (Anginer et al., 2014). This chapter uses the computational method outlined by Bharath and Shumway (2008); Fu et al. (2014). Equations (5.12) to (5.16) explain the computational method of the distance-to-default measure.

$$dd_{it} = N\left(-\frac{ln\left(\frac{V_{A,it}}{D_{it}}\right)+\left(u_{it}-\delta_{it}-\left(\frac{\sigma_{A,it}^{2}}{2}\right)\right)T}{\sigma_{A,it}\sqrt{T}}\right) \tag{5.12}$$

where dd is the distance-to-default, N is the cumulative normal distribution function, V_A is the value of total assets, D is total liabilities as measure of the face value of debt, u is the expected return, δ is the total dividend as a percentage of total value of the bank, σ_A is the standard deviation of total assets, and T is the time to maturity. The subscripts i and t denote each bank and quarter respectively. These are further defined below.

$$V_{A,it} = V_{E,it} + D_{it} \tag{5.13}$$

$$\sigma_{A,it} = \frac{V_{E,it}}{V_{A,it}}\sigma_{E,it} + \frac{D_{it}}{V_{A,it}}\sigma_{D,it} \tag{5.14}$$

$$\sigma_{D,it} = 0.05 + 0.25\sigma_{E,it} \tag{5.15}$$

$$u_{it} = r_{i,t-1} \tag{5.16}$$

where V_E is the market value of common equity, σ_E is the standard deviation of equity returns, σ_D is the standard deviation of total liabilities, and $r_{i,t-1}$ is stock returns over the previous quarter[13].

In terms of the calculation of volatility of debt (σ_D), Bharath and Shumway (2008) assume that the risk of debt is correlated with the risk of equity. Therefore, they include five percentage points in the equation (5.15) to represent the term structure volatility and 25 percent of the equity volatility to allow for volatility associated with risk of equity. This chapter follows the same procedure to calculate the volatility of debt.

The next two market-based measures focus on systemic stability instead of stability at the individual bank level. They take into account the interconnectedness of financial institutions. The logistic transformation of R-squared (logistic R-squared) and the change in conditional value at risk (CoVaR) are derived from the distance-to-default measure and examine each bank's contribution to the distress of the entire banking system as a whole. The logistic R-squared measures the total variation of default risk of a given bank explained by default risk of all the other banks in a given country. R-squared is obtained from regressing change in default risk for bank i in quarter t on average change in default risk of all other banks in quarter t excluding bank i (Anginer & Demirguc-Kunt, 2011, 2014; Anginer et al., 2014; Karolyi, Lee, & van Dijk, 2012; Morck, Yeung, & Yu, 2000).

$$\Delta dd_{it} = \alpha_{it} + \beta_{it}\frac{1}{n}\sum_{k=1,k\neq i}^{n}\Delta dd_{kt} + \varepsilon_{it} \tag{5.17}$$

[13] When the stock returns of the previous quarter are negative, replace the expected return with the treasury bill rate (risk-free rate) of the respective quarter (Fu et al., 2014).

The R-squared is obtained from estimation of equation (5.17) and the logistic R-squared is computed by making the transformation log $(\frac{R_{it}}{1-R_{it}})$. High R-squared values indicate that banks are exposed to similar sources of risks and that banks are inter-connected in a given country. Both interconnectedness and common exposure to risk makes the banking sector more unstable (Anginer et al., 2014).

The second systemic stability measure is the CoVaR. It estimates the contribution of each bank to overall systemic risk by following the CoVaR methodology of Adrian and Brunnermeier (2016). For each bank in the sample, a value at risk (VaR) measure is calculated at the first and fiftieth percentiles by the change in distance-to-default at those percentiles. The first percentile is when each bank is in the distress level, and the fiftieth percentile is of course the median. The change in distance-to-default/VaR variable is regressed on lagged state variables. Five state variables are used for the regression as outlined by Anginer et al. (2014): change in the term spread, change in the default spread, the implied volatility index (VIX), the S&P500 return, and change in the 3 month Treasury bill rate. Equations (5.18) to (5.20) explain the associated computational method.

$$\Delta dd_{it}^{P} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{it}, \; P = 1, 50; \tag{5.18}$$

$$\Delta Systemdd_t = \alpha_{system} + \beta_{system}\Delta dd_{it}^{1} + \gamma_{system}M_{t-1} + \varepsilon_{system,i,t}. \tag{5.19}$$

$$CoVaRsystem_{it} = \hat{\beta}_{system}\left(\widehat{\Delta dd_{it}^{1}} - \widehat{\Delta dd_{it}^{50}}\right). \tag{5.20}$$

In equation (5.18), the VaR/change in distance-to-default variable of each bank is regressed on the lagged state variables (M_{t-1}) -- first for a VaR measure calculated at the first percentile, then for a VaR measure calculated at the fiftieth percentile. In equation (5.19), the change in value-weighted, total distance-to-default of all banks is regressed on the change in distance-to-default of each bank i calculated at its first percentile (when a bank is in the distress level) and on the lagged state variables. Equation (5.20) computes the CoVaR of the system for bank *i* at time *t* as a function of the change in the estimated distance-to-default of bank *i* when the bank is at the 1st percentile minus its estimated distance-to-default when the bank is at the median percentile, where the estimated distance-to-default values come from equation (5.18).

5.5 Estimation Methods

This chapter uses fractional logistic estimation, correlated random effects, and ordinary least squares to estimate the relationship between financial stability and competition. Equation (5.21) specifies the respective regression equation. The estimation equations independently use five stability measures: Z-score, NPL, distance-to-default, logistic R-squared, and CoVaR.

$$Stability\ measure_{it} = \beta_0 + \beta_1 competition\ measure_{it} + \beta_2 bank\ controls_{it} + \beta_3 time\ dummies + \varepsilon_{it} \tag{5.21}$$

Z-score, NPL, and distance-to-default are all fractional variables. Z-score and distance-to-default produce inverse probabilities of default. NPL is a ratio of non-performing loans as a percentage of total loans. All three measures are restricted to the interval between 0 and 1. Papke and Wooldridge (1996) developed a fractional logistic estimation method for estimating models with dependent variables that represent shares or probabilities.

Four competition measures are used as the main explanatory variables in the estimation equations: H-statistic, the Lerner index, the Boone indicator based on marginal costs (Boone MC), and the Boone indicator based on average costs (Boone AC). H-statistic and the Boone indicator are time-constant competition measures for each bank. Hence, correlated random effects estimation is also used to estimate the regressions. According to

Wooldridge (2013), the correlated random effects procedure provides a way of including time-constant variables in a fixed effects framework.

Bank-level control variables are the total assets of the bank, non-interest income as a percentage of total income, and the ratio of net loans to total assets. The natural logarithm of total assets is used to control for the size of the bank. Large banks have the advantage of exploiting economies of scale and thus are expected to be more stable compared to small banks (Liu & Wilson, 2013; Schaeck & Cihak, 2014). The diversification of revenue is measured by the ratio of non-interest income to total income. The expansion into non-traditional financial services is associated with an increase in the volatility of revenue generation and believed to contribute to increasing operational risk (Kick & Prieto, 2015; Liu & Wilson, 2013). Banks with relatively high loans to assets ratios are more illiquid (Chronopoulos, Liu, McMillan and Wilson, 2015). This is supported by some papers that present evidence that an increase in loans to assets decreases stability (Leroy & Lucotte, 2017; Liu & Wilson, 2013). On the other side are papers that argue that an increase in loans to assets can contribute to greater stability if this indicates the acquisition of high-quality assets (Amidu, 2013; Soedarmono, Machrouh, & Tarazi, 2013; Turk-Ariss, 2010). Time dummies are included to capture unobserved factors that change over time and that are common across all the banks in the sample.

5.6 Data

This chapter collects data from multiple sources. Quarterly accounting data of commercial banks in the USA are obtained from the Standard & Poor's Global Market Intelligence platform SNL Financial (SNL) The SNL is selected over other databases since it provides wider coverage to access data for last 17 years. The other available databases such as Bloomberg, Orbis allowed obtaining data for 10 years. In SNL, the availability of observations prior to year 2000 is very limited and due to that reason the sample period of the study is restricted from 2000 to 2017. Historical data are available for active commercial banks in 2017 and the final sample consists of 883 banks for 72 quarters. This is an unbalanced sample. The bank-level competition measures are calculated using time series regressions and an adequate number of observations are required to calculate all competition measures for each bank. Hence, this chapter uses quarterly data for each bank instead of annual data. All the variables are winsorized to reduce the influence of outliers.

Market-based data are collected from the Center for Research in Security Prices (CRSP). It provides an accurate, survivor bias-free historical stock market data. Quarterly averages of the 3-month Treasury bill rate, the default spread (TED spread), and long term government bond yields are obtained from the Federal Reserve Bank of St. Louis. The volatility index (VIX) is collected from Chicago Board Options Exchange. S&P 500 prices are obtained from Yahoo Finance. The concentration ratio for the USA is available from the Global Financial Development Database, but only until year 2015[14].

5.7 Results

5.7.1 Pairwise correlations

H-statistic, Lerner index, Boone MC, and Boone AC are the four measures of competition used in this analysis. The H-statistic assumes that the market is in equilibrium. The long-run equilibrium condition for the H-statistic is tested via estimation of equation (5.3) (Claessens & Laeven, 2004; Goddard & Wilson, 2009; Schaeck et al., 2009). The p-value of the associated F-test is 0.3778 (see above). As a result, one cannot reject the null

[14] Data and codes to replicate the results of the chapter are available on https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FE6CC3V or https://github.com/SamangiBandaranayake/Bank-Competition-and-Financial-Stability-USA

hypothesis that the banking system in the USA was in long-run equilibrium during the period of study of this analysis.

Tables 5.1A, 5.1B and 5.1C report pairwise correlations for the four competition measures. In Table 5.1A, the sample sizes differ for each pair of correlations. In tables 5.1B and 5.1C, correlations are calculated over a common set of observations. Tables 5.1A and 5.1B use the Boone indicator calculated with marginal costs. Table 5.1C repeats the analysis, replacing the Boone indicator using marginal costs with the Boone indicator calculated with average costs. While the pairwise correlations are small in size, they are all highly significant, no doubt due in part to the large sample sizes. The low correlations indicate that these measures, though all intended to measure the same thing, are at best picking up different aspects of competition, or at worst are in one or more instances poorly measuring competition (Leon, 2015).

The Lerner index is constructed to decrease as competition increases, while H-statistic is designed to increase as the degree of competition increases. Accordingly, as expected, the Lerner index is negatively correlated with H-statistic in all three tables. Like the Lerner index, the Boone indicator is constructed to decrease in value with increasing competition. As also expected, both versions of the Boone indicator are positively associated with the Lerner index. Interestingly, both Lerner and Boone MC are based on marginal costs and the associated pairwise correlation between these two variables (approximately 0.24 in tables 5.1A and 5.1B) is larger than the pairwise correlation using the average costs version of the Boone indicator (approximately 0.13, see table 5.1C). However, contrary to expectations, the Boone indicator – both versions -- are positively correlated with H-statistic. While it is somewhat unusual that two variables are positively associated with each but have a differently signed correlations with a third variable, it is certainly possible, and straightforward examples can be easily produced.

Table 5.1A

Pairwise Correlations

	H-statistic	Lerner	Boone MC
H-statistic	- - Obs=63866		
Lerner	-0.0626 p-value=0.000 Obs=45975	- - Obs=46040	
Boone MC	0.1537 p-value=0.000 Obs=46123	0.2420 p-value=0.000 Obs=45953	- - Obs=46187

Note. This table considers the H-statistic, Lerner index and Boone MC as the competition measures. H-statistic, Lerner, and Boone MC are described in the text. Number of pairwise observations differ because the availability of data.

Table 5.1B

Pairwise Correlations with Common Observations

	H-statistic	Lerner	Boone MC
H-statistic	- - Obs=41030		
Lerner	-0.0600 p-value=0.000 Obs=41030	- - Obs=41030	
Boone MC	0.1537 p-value=0.000 Obs=41030	0.2482 p-value=0.000 Obs=41030	- - Obs=41030

Note. This table considers the H-statistic, Lerner index and Boone MC as the competition measures. H-statistic, Lerner, and Boone MC are described in the text.

Table 5.1C

Pairwise Correlation with Common Observations

	H-statistic	Lerner	Boone AC
H-statistic	- - Obs=41030		
Lerner	-0.0600 p-value=0.000 Obs=41030	- - Obs=41030	
Boone AC	0.0392 p-value=0.000 Obs=41030	0.1309 p-value=0.000 Obs=41030	- - Obs=41030

Note. This table considers the H-statistic, Lerner index and Boone AC as the competition measures. H-statistic, Lerner, and Boone AC are described in the text.

5.7.2 Evaluating the impact of competition on stability

The impact of bank competition on financial stability is estimated using both fractional logistic estimation and correlated random effects. Tables 5.2 to 5.7 report the results using three stability measures as the dependent variable: Z-score, NPL ratio, and distance-to-default.

5.7.2.1 Z-score as the stability measure

Table 5.2 reports estimates of various specifications of the relationship between stability and competition. In each specification, the dependent variable is Z-score, with increases in Z-score indicating greater financial stability. Columns (1) through (4) report the results of specifications that include each competition variable separately. Columns (5) and (6) combine H-statistic, Lerner, and Boone in a single specification. Column (5) uses Boone MC as the Boone indicator, and column (6) uses Boone AC as the Boone indicator. The H-statistic measure is designed to increase with greater competition. The Lerner and Boone measures are decreasing in greater competition.

Beginning with column (1) and H-statistic, the sign of the coefficient suggests a negative association between competition and stability. However, the associated t-statistic is -0.63, so this is a weak result. The results for the other competition measures are stronger. The estimated coefficients for Lerner, Boone MC, and Boone AC, are statistically significant at the 5-percent level in columns (2)-(6). The positive coefficients indicate that these competition measures are also negatively associated with financial stability. These findings are in line with those reported in Agoraki et al. (2011); A. Kasman and S. Kasman (2015).

Bank size ("Assets") is measured by the natural logarithm of total assets and is positively associated with bank stability, consistent with previous studies (Beck et al., 2013). Income diversification, represented by "Non-interest", shows a negative association with Z-score, also consistent with previous studies (Beck et al., 2013; Leroy & Lucotte, 2017; Liu et al., 2013). When a bank expands into non-traditional financial services, this can increase the volatility of revenue generation, which in turn can contribute to instability (Kick & Prieto, 2015; Liu & Wilson, 2013). A negative coefficient of loans to total assets ("Loans") can signal illiquidity problems associated with higher debt. Liu and Wilson (2013) report a similar finding for the Japanese banking sector, confirming that a higher proportion of loans to assets increases the default risk of the bank.

Table 5.2

Effect of Bank Competition on Financial Stability (Z-score as the Stability Measure)

	(1)	(2)	(3)	(4)	(5)	(6)
H-statistic	-0.0478				-0.0841	-0.0264
	(0.0758)				(0.0760)	(0.0758)
Lerner		0.4391***			0.2513**	0.3697***
		(0.1135)			(0.1122)	(0.1082)
Boone MC			0.1105***		0.1071***	
			(0.0125)		(0.0131)	
Boone AC				4.4317***		4.3143***
				(0.6600)		(0.6739)
Assets	0.0913***	0.0843***	0.0777***	0.0752***	0.0768***	0.0710***
	(0.0119)	(0.0117)	(0.0116)	(0.0115)	(0.0120)	(0.0119)
Non-interest	-0.7594***	-0.7804***	-0.9259***	-0.7385***	-0.9305***	-0.7563***
	(0.1520)	(0.1524)	(0.1514)	(0.1547)	(0.1530)	(0.1569)
Loans	-0.4809***	-0.4513***	-0.4188***	-0.4580***	-0.3826***	-0.4194***
	(0.1460)	(0.1459)	(0.1410)	(0.1454)	(0.1415)	(0.1454)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	41,252	41,094	41,315	41,315	41,030	41,030
Banks	880	874	882	882	871	871

Note. The table reports estimation results from the fractional logistic estimation. The dependent variable is the Z-score. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. Column (1) uses H-statistic; column (2) uses Lerner index; column (3) uses Boone MC; and column (4) uses Boone AC as competition variable in the respective specifications. Columns (5) and (6) estimate the regression with all the competition measures. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 5.3 follows the same specifications as Table 5.2 but estimates the models with correlated random effects. The results are generally similar to those in Table 5.2, with two exceptions. The first exception is that H-statistic is now statistically significant in some of the specifications. This confirms the results from Table 5.2 that showed a consistently negative relationship between competition and stability.

The second exception concerns the Loans variable. Unlike the previous estimation, the estimated coefficient for this variable is positive, indicating that an increase in the ratio of loans to total assets is positively associated with stability. Other studies have also found this on occasion and explain it by saying that this suggests that the bank's loan portfolio contains high-quality loans, and more high-quality loans contribute to greater financial stability (Amidu, 2013; Soedarmono et al., 2013; Turk-Ariss, 2010).

According to the results of Tables 5.2 and 5.3, when Z-score is used as the stability measure, the associated estimation finds that competition is negatively associated with financial stability. This supports the competition-fragility hypothesis.

Table 5.3

Effect of Bank Competition on Financial Stability (Z-score as the Stability Measure)

	(1)	(2)	(3)	(4)	(5)	(6)
H-statistic	-0.0009*				-0.0011**	-0.0007
	(0.0005)				(0.0005)	(0.0005)
Lerner		0.0022***			0.0016**	0.0019**
		(0.0008)			(0.0008)	(0.0008)
Boone MC			0.0004***		0.0004***	
			(0.0007)		(0.0001)	
Boone AC				0.0237***		0.0232***
				(0.0039)		(0.0039)
Assets	0.0007***	0.0007***	0.0006***	0.0006***	0.0006***	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Non-interest	-0.0020***	-0.0021***	-0.0022***	-0.0021***	-0.0022***	-0.0021***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Loans	0.0038***	0.0038***	0.0038***	0.0038***	0.0038***	0.0038***
	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	41,252	41,094	41,315	41,315	41,030	41,030
Banks	880	874	882	882	871	871

Note. The table reports estimation results from the correlated random effects estimation. The dependent variable is the Z-score. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. Column (1) uses H-statistic; column (2) uses Lerner index; column (3) uses Boone MC; and column (4) uses Boone AC as competition variable in the respective specifications. Columns (5) and (6) estimate the regression with all the competition measures. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

5.7.2.2 NPL as the stability measure

Tables 5.4 and 5.5 repeat the analysis of Tables 5.2 and 5.3 except they use the NPL ratio as the dependent variable. Increases in NPL indicate decreased financial stability. In Table 5.4, the estimated coefficient for H-statistic is positive, suggesting that competition is negatively associated with stability, however the estimated coefficient never achieves a 5-percent significance level.

In contrast, the positive and significant coefficients for Lerner and Boone MC indicate that banks in less competitive banking sectors tend to have a greater proportion of non-performing loans, and thus are less stable. This supports the competition-stability hypothesis and is in line with the empirical findings of Berger et al. (2009). The Boone AC coefficients, while differently signed from the Boone MC coefficients, have large standard errors so that little can be concluded from these.

With respect to the control variables, bank size ("Assets") again displays a positive and significant association with financial stability. This is consistent with large banks being able to maintain stable loan portfolios, resulting in a low credit risk (Agoraki et al., 2011). The other control variables never achieve statistical significance.

The correlated random effects results of the same specifications are reported in Table 5.5. While most of the results are qualitatively the same, there are three differences. First, H-statistic, while still indicating a negative association with financial stability, is now significant at the 5-percent level in two of the regressions. The second difference is that Lerner now falls to statistical insignificance in all the regressions in which it appears. And the last difference is that Loans is now statistically significant across all six regressions. The negative coefficient indicates that a higher loan to assets ratio is associated with fewer non-performing loans. This is consistent with the findings from table 5.3.

In summary, the results using NPL as a dependent variables are somewhat different from those using Z-score as a measure of stability, particularly with respect to the Lerner and Boone competition variables. This confirms the findings of Zigraiova and Havranek (2016) who found that the sign of the estimated relationship between bank competition and stability depends on the measure of stability, among other things.

Table 5.4

Effect of Bank Competition on Financial Stability (NPL as the Stability Measure)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H-statistic	0.2037*				0.1354	0.1892*
	(0.1074)				(0.1032)	(0.1051)
Lerner		0.3354**			0.2214	0.3742**
		(0.1437)			(0.1489)	(0.1469)
Boone MC			0.0931***		0.0771***	
			(0.0252)		(0.0258)	
Boone AC				-0.4862		-0.5781
				(1.2971)		(1.3044)
Assets	-0.0404**	-0.0364**	-0.0481**	-0.0310	-0.0521***	-0.0416**
	(0.0186)	(0.0180)	(0.0193)	(0.0193)	(0.0195)	(0.0201)
Non-interest	-0.0294	0.0087	-0.1703	0.0075	-0.1701	-0.0323
	(0.2241)	(0.2299)	(0.2237)	(0.2274)	(0.2233)	(0.2260)
Loans	-0.1009	-0.0616	0.0051	-0.0978	0.0016	-0.0755
	(0.2035)	(0.2081)	(0.2077)	(0.2074)	(0.2072)	(0.2069)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	44,008	43,876	44,072	44,072	43,811	43,811
Banks	877	872	879	879	869	869

Note. The table reports estimation results from the fractional logistic estimation. The dependent variable is the NPL. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. Column (1) uses H-statistic; column (2) uses

Lerner index; column (3) uses Boone MC; and column (4) uses Boone AC as competition variable in the respective specifications. Columns (5) and (6) estimate the regression with all the competition measures. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 5.5

Effect of Bank Competition on Financial Stability (NPL as the Stability Measure)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H-statistic	0.0055**				0.0030	0.0047**
	(0.0021)				(0.0020)	(0.0021)
Lerner		-0.0015			-0.0032	-0.0013
		(0.0031)			(0.0032)	(0.0032)
Boone MC			0.0018***		0.0017***	
			(0.0005)		(0.0005)	
Boone AC				0.0076		0.0113
				(0.0259)		(0.0264)
Assets	-0.0025***	-0.0023***	-0.0026***	-0.0024***	-0.0025***	-0.0024***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Non-interest	-0.0024	-0.0027	-0.0026	-0.0021	-0.0033	-0.0029
	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0042)
Loans	-0.0143***	0.0143***	-0.0141***	-0.0143***	-0.0142***	-0.0144***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0041)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	44,008	43,876	44,072	44,072	43,811	43,811
Banks	877	872	879	879	869	869

Note. The table reports estimation results from the correlated random effects estimation. The dependent variable is the NPL. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. Column (1) uses H-statistic; column (2) uses Lerner index; column (3) uses Boone MC; and column (4) uses Boone AC as competition variable in the respective specifications. Columns (5) and (6) estimate the regression with all the competition measures. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

5.7.2.3 Distance-to-default as the stability measure

The measure of stability used in the estimation of Tables 5.6 and 5.7 is distance-to-default. These tables follow the same specifications and estimation methods as the previous tables. Like Z-score, distance-to-default measures the inverse probability of default, so that increases in this variable are associated with greater financial stability. Distance-to-default is a market-level measure requiring stock market data. As not all banks are listed, this limits the number of observations available for estimation. The analysis here uses 359banks.

As in previous tables, H-statistic is negatively associated with financial stability in Tables 5.6 and 5.7. However, the respective coefficients are never significant at the 5-percent level. Similarly, decreases in competition as measured by Lerner, Boone MC, and Boone AC are associated with increased stability, though again none of the estimated coefficients are significant. From the bank-level control variables, only size of bank (“Assets”) is statistically significant, and that only in some of the specifications of table 5.6. As before, the results indicate that larger banks are more stable.

In summary, the results from regressions using distance-to-default as a measure of financial stability are generally statistically insignificant. The only variable which achieves significance, and that only in a few regressions, is bank size. None of the competition variables achieve statistical significance at the 5-percent level, though the signs of the coefficients indicate that greater competition reduces stability.

Table 5.6

Effect of Bank Competition on Financial Stability (Distance-to-default as the stability measure)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H-statistic	-0.0904*				-0.0878*	-0.0878*
	(0.0494)				(0.0493)	(0.0493)
Lerner		0.0577			0.0262	0.0380
		(0.0928)			(0.0955)	(0.0955)
Boone MC			0.0079		0.0073	
			(0.0054)		(0.0056)	
Boone AC				0.0717		0.0491
				(0.2017)		(0.1929)
Assets	0.0215**	0.0192*	0.0109*	0.0193*	0.0218**	0.0211**
	(0.0108)	(0.0107)	(0.0107)	(0.0107)	(0.0108)	(0.0108)
Non-interest	-0.1051	-0.1163	-0.1325	-0.1147	-0.1211	-0.1051
	(0.1536)	(0.1554)	(0.1551)	(0.1549)	(0.1533)	(0.1533)
Loans	-0.1248	-0.1318	-0.1333	-0.1369	-0.1180	-0.1202
	(0.1484)	(0.1536)	(0.1527)	(0.1530)	(0.1487)	(0.1490)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	10,032	10,032	10,032	10,032	10,032	10,032
Banks	359	359	359	359	359	359

Note. The table reports estimation results from the fractional logistic estimation. The dependent variable is the distance-to-default. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. Column (1) uses H-statistic; column (2) uses Lerner index; column (3) uses Boone MC; and column (4) uses Boone AC as competition variable in the respective specifications. Columns (5) and (6) estimate the regression with all the competition measures. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 5.7

Effect of Bank Competition on Financial Stability (*Distance-to-default as the stability measure)*

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H-statistic	-0.0174*				-0.0160	-0.0160
	(0.0098)				(0.0098)	(0.0098)
Lerner		0.0240			0.0179	0.0208
		(0.0174)			(0.0176)	(0.0177)
Boone MC			0.0014*		0.0012	
			(0.0008)		(0.0008)	
Boone AC				0.0064		0.0012
				(0.0338)		(0.0326)
Assets	0.0012	0.0007	0.0009	0.0008	0.0012	0.0010
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Non-interest	0.0129	0.1024	0.0093	0.0111	0.0108	0.0122
	(0.0286)	(0.0286)	(0.0287)	(0.0287)	(0.0286)	(0.0286)
Loans	0.0010	0.0018	0.0007	0.0003	0.0025	0.0024
	(0.0306)	(0.0310)	(0.0309)	(0.0310)	(0.0307)	(0.0307)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	10,032	10,032	10,032	10,032	10,032	10,032
Banks	359	359	359	359	359	359

Note. The table reports estimation results from the correlated random effects estimation. The dependent variable is the distance-to-default. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. Column (1) uses H-statistic; column (2) uses Lerner index; column (3) uses Boone MC; and column (4) uses Boone AC as competition variable in the respective specifications. Columns (5) and (6) estimate the regression with all the competition measures. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

5.7.3 Estimation of the effect size

This section translates the estimation results of the previous section into economically meaningful numbers. Table 5.8 reports estimated effects for the fractional logistic regression model, and Table 5.9 does the same for the correlated random effects model. In each table, the economic effects associated with H-statistic, Lerner, Boone MC, and Boone AC are calculated from columns (1) through (4) of the respective regressions in Table 5.2 through 5.7. In other words, the economic effects come from specifications in which the respective competition variable is the only competition variable in the regression. To estimate the economic effects, each of the competition variables are increased from their 25th percentile value to their 75th percentile value, while the control variables are held constant at their mean values. The economic effect is calculated as the associated change in the predicted value of the dependent variable. Each table has three panels, depending on the respective measure of stability: Z-score (panel A), NPL (panel B), and distance-to-default (panel C). The mean of the respective dependent variables are reported in each panel to provide a numerical context for the size of the associated change in the dependent variable.

In panel A of Table 5.8, an increase in the H-statistic from its 25th to 75th percentile value reduces the inverse probability of default by 0.01 percentage points. In panel B, a similarly-sized change in H-statistic is associated with an increase in NPL of 0.13 percentage points. And in panel C, the same change in H-statistic is associated with a decrease in distance-to-default of 0.66 percentage points. The associated mean values for Z-score, NPL, and distance-to-default are 0.58, 1.82, and 72.77 percent, respectively. These provide a numerical context for assessing the respective size of the changes. As such it is clear that the predicted changes in the stability measures resulting from an increase in H-statistic from its 25th to 75th percentile value are very, very small. Further, the underlying coefficient estimates for H-statistic that are used to calculate these are in each instance statistically insignificant, so that one cannot reject the possibility that the associated economic effects are nil.

Table 5.8 calculates the economic effects for the other three competition variables associated with a change in the respective competition variables from their 25th to 75th percentile values. If anything, the estimated effects are even smaller. For the Lerner index, the change in the stability measure, rounded to two significant digits, is 0.00 percentage points for all three panels. For Boone MC, they range from 0.07 to 0.18 percentage points; and for Boone AC, they range from -0.02 to 0.06 percentage points. In terms of economic significance, these changes are negligible.

Table 5.9 repeats the same exercise as Table 5.8, except that the underlying effects are calculated from the correlated random effects regression models. While the numbers change somewhat, the overall conclusion is identical: The predicted, economic effects on financial stability associated with changes in the competition variables from their 25th to 75th percentile values are negligible.

Table 5.8

Effect Size Estimates at the 25th, 50th, and 75th Percentile Values of H-statistic, Lerner, Boone MC, and Boone AC

	H-statistic	**Lerner**	**Boone MC**	**Boone AC**
Panel A: Stability measure = Z-score (Mean = 0.0058)				
25th percentile	0.0058	0.0059	0.0055	0.0054
50th percentile	0.0057	0.0059	0.0059	0.0057
75th percentile	0.0057	0.0059	0.0062	0.0060
Δ 75th - 25th	***-0.0001***	***0.0000***	***+0.0007***	***+0.0006***
Obs	41,252	41,094	41,315	41,315
Panel B: Stability measure = NPL (Mean = 0.0182)				
25th percentile	0.0176	0.0185	0.0179	0.0183
50th percentile	0.0182	0.0185	0.0188	0.0182
75th percentile	0.0189	0.0185	0.0197	0.0181
Δ 75th - 25th	***+0.0013***	***0.0000***	***+0.0018***	***-0.0002***
Obs	44,008	43,876	44,072	44,072
Panel C: Stability measure = Distance-to-default (Mean = 0.7277)				
25th percentile	0.7311	0.7283	0.7274	0.7275
50th percentile	0.7282	0.7283	0.7281	0.7278
75th percentile	0.7245	0.7283	0.7288	0.7279
Δ 75th - 25th	***-0.0066***	***0.0000***	***+0.0014***	***+0.0004***
Obs	10,032	10,032	10,032	10,032

Note. The predicted probabilities are derived from the fractional logistic model of Table 5.2, 5.4, and 5.6. The dependent variable in Panels A, B, and C are Z-score, NPL and the distance-to-default. All probabilities are calculated at the mean values of the regression covariates, except for the variable of interest (H-statistic, Lerner, Boone MC, or Boone AC) which are evaluated at their 25th, 50th, and 75th percentile values.

Table 5.9

Effect Size Estimates at the 25th, 50th, and 75th Percentile Values of H-statistic, Lerner, Boone MC, and Boone AC

	H-statistic	**Lerner**	**Boone MC**	**Boone AC**
Panel A: Stability measure = Z-score (0.0058)				
25th percentile	0.0058	0.0058	0.0056	0.0054
50th percentile	0.0057	0.0058	0.0058	0.0057
75th percentile	0.0055	0.0058	0.0060	0.0060
Δ 75th - 25th	***-0.0003***	***0.0000***	***+0.0004***	***+0.0006***
Obs	41,252	41,094	41,315	41,315
Panel B: Stability measure = NPL (Mean = 0.0182)				
25th percentile	0.0166	0.0175	0.0175	0.0175
50th percentile	0.0175	0.0175	0.0184	0.0176
75th percentile	0.0185	0.0175	0.0193	0.0177
Δ 75th - 25th	***+0.0019***	***0.0000***	***+0.0018***	***-0.0002***
Obs	44,008	43,876	44,072	44,072
Panel C: Stability measure = Distance-to-default (Mean = 0.7277)				
25th percentile	0.7292	0.7272	0.7257	0.7258
50th percentile	0.7262	0.7272	0.7263	0.7259
75th percentile	0.7225	0.7272	0.7269	0.7260
Δ 75th - 25th	***-0.0067***	***0.0000***	***+0.0012***	***+0.0002***
Obs	10,032	10,032	10,032	10,032

Note. The predicted probabilities are derived from the correlated random effects estimation of Table 5.3, 5.5, and 5.7. The dependent variable in Panels A, B, and C are Z-score, NPL and the distance-to-default. All probabilities are calculated at the mean values of the regression covariates, except for the variable of interest (H-statistic, Lerner, Boone MC, or Boone AC) which are evaluated at their 25th, 50th, and 75th percentile values.

5.8 Robustness Tests

This section performs two robustness checks. The first robustness test excludes the Global Financial Crisis (GFC) period from the analysis. The second robustness test includes bank concentration in the respective regression specifications. The analysis restricts itself to three competition measures: H-statistic, the Lerner index, and Boone MC.

5.8.1 Exclusion of the Global Financial Crisis Episodes

Calderon and Schaeck (2016) describe the effect of government aid programmes on competition in the banking sector during the GFC period. Their findings indicate that, during this period, government aid programmes contributed to an increase in bank competition. Furthermore, they affected the relationship between competition and stability. To eliminate the impact of massive bailout programmes, Section 5.8.1 excludes the GFC period and post-GFC period and re-estimates the key models for a restricted sample period. The recession in US started in fourth quarter of 2007. Due to that the pre-crisis sample period ending in third quarter of 2007.

Table 5.10 re-estimates the specification of column (5) in Tables 5.2-5.7. Panel A reports results from the fractional logistic estimation, and panel B reports results from the correlated random effects estimation. Most of the competition variables are not significant. There are four regressions where they are: Boone MC in the Z-score regressions of columns (1) and (4), Lerner in the Z-score regression of column (1), H-statistic in the Z-score regression of column (4), and Boone MC in the NPL regressions columns (2) and (5). In the Z-score regressions, the signs of the estimated coefficients indicate a negative relationship between competition and stability. In the NPL regressions, they indicate a positive relationship. Thus, the exclusion of the GFC and post-GFC periods confirm the same, conflicting results that were obtained using the full sample period.

Table 5.10

Exclusion of the GFC Period

	Panel A: Fractional logistic estimation			Panel B: Correlated random effects estimation		
	Z-score	**NPL**	**D-t-D**	**Z-score**	**NPL**	**D-t-D**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H-statistic	-0.1419	0.1550	-0.0760	-0.0010**	0.0018	-0.0093
	(0.0896)	(0.1106)	(0.0633)	(0.0005)	(0.0027)	(0.0128)
Lerner	0.3101**	0.1482	-0.0381	0.0015*	-0.0074*	0.0013
	(0.1346)	(0.1602)	(0.1148)	(0.0009)	(0.0045)	(0.0243)
Boone MC	0.0863***	0.0870***	0.0081*	0.0004***	0.0018***	0.0011
	(0.0146)	(0.0266)	(0.0048)	(0.0001)	(0.0006)	(0.0008)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	28,969	27,615	6,350	28,969	27,615	6,350
Banks	866	864	355	866	864	355

Note. The table restricts the sample period from Q1-2000 to Q3-2007. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 5.11

Competition and Concentration Interaction

	Z-score			NPL			Distance-to-default		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
H-statistic	-0.0005 (0.0023)			-0.0024 (0.0074)			-0.0504 (0.0716)		
H-statistic*Con	-0.0007 (0.0071)			0.0291 (0.0261)			0.0721 (0.2328)		
Lerner		-0.0009 (0.0043)			0.0076 (0.0153)			-0.0320 (0.1481)	
Lerner*Con		0.0081 (0.0124)			-0.0270 (0.0476)			0.2108 (0.4726)	
Boone MC			-0.0017*** (0.0005)			-0.0046 (0.0031)			0.0164 (0.0189)
Boone*Con			-0.0036 (0.0016)			0.0195** (0.0093)			-0.0447 (0.0540)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	35,342	35,224	35,389	38,594	38,475	38,642	8,263	8,263	8,263

Note. The table reports estimation results from the correlated random effects estimation. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

5.8.2 Inclusion of bank concentration

As a further robustness check, this section includes an interaction of the three-bank concentration ratio with each of the three competition variables. The purpose is to see if concentration mediates the relationship between competition and stability in line with the findings of Schaeck et al. (2009). They report evidence that concentrated banking sectors accentuate the positive effects of competition on stability. Data on the three-bank concentration ratio are available from the Global Financial Development Database through 2015. As a result, the empirical analysis for this section only extends through that year.

Table 5.11 reports the results of this analysis. In each column, interaction terms for concentration were added to the specifications of columns (1) to (3) in Tables 5.2 through 5.7, respectively. Of the nine interaction terms, only one is statistically significant – the interaction term for Boone in column (6). One should not make too much out of a single significant coefficient (out of 9). However, it can be noted that the direction of the effect is the same as what Schaeck et al. (2009) found: concentrated banking sectors accentuate the positive effects of competition on stability, at least when competition is measured by the Boone indicator and stability is measured by NPL.

5.9 Systemic Stability

This section examines the effect of competition on systemic stability. Logistic R-squared and the change in CoVaR estimate the interconnectedness of banks and the common exposure to the risk (Anginer et al., 2014).

The dependent variable in Table 5.-12 is logistic R-squared. The main explanatory variables in specifications (1) to (4) are H-statistic, Lerner, Boone MC, and Boone AC, respectively. Specifications (5) and (6) include all the competition measures in one specification. Column (5) uses Boone MC as the Boone indicator, and column (6) uses Boone AC as the Boone indicator.

Anginer et al. (2014) find that the relationship between Lerner and Logistic R-squared is positive and support competition-stability hypothesis. The results of Table 5.12 do not support their finding. All the competition coefficients are statistically insignificant at the 5-percent level. Further, all the control variables are also insignificant, with the exception of Assets, which is negatively and significantly associated with systemic stability in -four of the six regressions. Here, a negative coefficient here indicates that bank size is positively associated with financial stability, which is different to what Anginer et al. (2014) report.

Table 5.12

Effect of Bank Competition on Systemic Stability (Logistic R-squared as the Systemic Stability Measure)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
H-statistic	-0.4984				-0.6266	-0.5986
	(0.4572)				(0.4643)	(0.4651)
Lerner		-1.3906			-1.4171	-1.5841*
		(0.8789)			(0.9579)	(0.8580)
Boone MC			-0.1281		-0.0922	
			(0.1048)		(0.1159)	
Boone AC				4.3491		4.5696
				(4.6226)		(4.6192)
Assets	-0.1648**	-0.1609**	-0.1707**	-0.1847**	-0.1446*	-0.1566*
	(0.0837)	(0.0818)	(0.0829)	(0.0837)	(0.0830)	(0.0844)
Non-interest	-0.1575	-0.2723	-0.0517	-0.1648	-0.0458	-0.1132
	(0.8891)	(0.8734)	(0.9027)	(0.8914)	(0.8884)	(0.8622)
Loans	0.5437	0.2362	0.3909	0.5128	0.2910	0.3653
	(0.7190)	(0.7489)	(0.7306)	(0.7301)	(0.7241)	(0.7262)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20,555	20,555	20,555	20,555	20,555	20,555
Banks	350	350	350	350	350	350

Note. The table reports estimation results from the ordinary least squares estimation. The dependent variable is the logistic R-squared. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

Table 5.13 employs the same specifications as Table 5.1-2 except that CoVaR is used as the dependent variable. Once again, none of the competition variables are statistically significant. Further, now not even any of the control variables are significant. One possible reason for this null finding is the large reduction in the sample size, which reduces the statistical power of the regressions.

Table 5.13

Effect of Bank Competition on Systemic Stability (CoVaR as the Systemic Stability Measure)

	(1)	(2)	(3)	(4)	(5)	(6)
H-statistic	-0.8140				-0.7413	-0.8407
	(3.3531)				(3.3846)	(3.3535)
Lerner		-0.3358			-0.3585	-0.3423
		(1.0594)			(1.0583)	(1.0596)
Boone MC			0.4965		0.4949	
			(0.5195)		(0.5250)	
Boone AC				0.1210		0.0151
				(6.3208)		(6.4006)
Assets	0.0680	0.0725	0.0669	0.0673	0.0730	0.0732
	(0.1014)	(0.1079)	(0.1012)	(0.1012)	(0.1080)	(0.1080)
Non-interest	-0.1111	-0.0960	-0.1157	-0.1122	-0.0974	-0.0946
	(0.3233)	(0.3304)	(0.3238)	(0.3239)	(0.3294)	(0.3295)
Loans	0.9986	1.0034	0.9996	0.9987	1.0044	1.0033
	(0.7481)	(0.7471)	(0.7481)	(0.7481)	(0.7472)	(0.7472)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	8,753	8,753	8,753	8,753	8,753	8,753
Banks	315	315	315	315	315	315

Note. The table reports estimation results from the correlated random effects estimation. The dependent variable is the change in CoVaR. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on bank.

5.10 Conclusion

This chapter examines the relationship between bank competition and financial stability using bank-level data for the USA for the period 2000 and 2017. The analysis uses three common measures of bank competition: H-statistic, the Lerner index and the Boone indicator. Bank-level stability is also measured using alternative measures: Z-score, NPL, and distance-to-default. Logistic R-squared and the change in CoVaR are used as measures of systemic stability.

Interestingly, this chapter finds that the different measures of competition are only weakly correlated. Further, it finds that the effect of competition on stability varies with the measure of stability. When Z-score is used as the stability measure, the competition measures H-statistic, Lerner, and Boone generally evidence a negative relationship between competition and financial instability. This is also true when distance-to-default is used to measure stability, though the estimated coefficients are never significant at the 5-percent level. However, when NPL is used to measure bank-level stability, the results differ. Both the Lerner and Boone measures are associated with a positive relationship between competition and stability. H-statistic is consistently insignificant. The results using systemic stability measures are also statistically insignificant.

Bank size is positively associated with stability and the findings are consistent irrespective of the measure used for stability. Income diversification is statistically significant only when Z-score is used to measure stability. The estimates indicate that an increase in the volatility of revenue generation reduces stability. The loan to assets ratio is positively associated with stability in most of the estimations. However, it shows a negative association when fractional logistic estimation is used.

To determine the economic significance of the respective estimates, the estimated equations were used to predict the effect on stability of an increase in the respective competition variables from their 25^{th} to their 75^{th} percentile values. Across the board, the associated economic effects were very, very small. Even when the competition variables were statistically significant, the size of their economic effects was negligible.

This chapter performs two robustness checks. It excludes the GFC period from the analysis, and includes bank concentration. Excluding the GFC and following years does not change the conclusions obtained from the full sample. Further, while previous research found that concentration mediated the relationship between competition and stability (Schaeck et al., 2009), little evidence was found in this study to support that. Finally, expanding the analysis to estimate the relationship between bank competition and systemic stability did not produce any significant findings.

Zigraiova and Havranek (2016) show that the relationship between bank competition and financial stability changes with the definition of the measure used for stability. This chapter presents clear evidence supporting their finding. Overall, no consistent evidence relating bank competition and financial stability was found using these data on US banks.

5.11 Limitations of the study

There are two limitations in this chapter. First, due to the data availability, this study limits its focus to active banks in 2017. Therefore, the selected sample of the study includes banks which survived during the GFC period or any bank which commenced its operations at any date prior to 2017. This sample is affected with survivorship bias and the results of the chapter are derived from a survivor sample. Previous empirical investigations based on bank level data also highlight that the survivorship bias as a limitation of bank level studies (Delis & Kouretas, 2011; Demirguc-Kunt, Detragiache, & Gupta, 2000).

Second, the measures of competition are constructed using time series data. That generates time constant competition measures for each bank. The data availability issue prevents the computation of time varying competition measures. The empirical literature on bank competition use a constant measure of competition to examine the relationship between bank competition and financial stability (Berger et al., 2009; Bikker & Haaf, 2002a; Schaeck et al., 2009) and this study follows the same approach. It restricts the ability to capture the timely effect of changes in competition.

Chapter Six

6.1 Introduction

This chapter presents a brief summary of the thesis. The main aim of the thesis was to examine the relationship between bank competition and financial stability. This goal was categorised into three specific research questions; (i) Are competitive banking systems really more stable? (ii) What is the effect of bank competition on financial stability? (iii) How does competition affect financial stability? The remainder of this chapter explains the findings for each question.

6.2 Are Competitive Banking Systems Really More Stable?

Chapter 2 of this thesis attempted to respond to the first question doing a replication of Schaeck et al. (2009). This is a country-level analysis of bank competition and financial stability. The main explanatory variables are Panzar and Rosse (1987) H-statistic and the three-bank concentration ratio. The replication consisted of six steps.

Firstly, the results were re-estimated with data provided by the authors. The replicated results closely matched the published results. In the second step, the control variables were updated using multiple data sources, and the replication was continued using the updated data. It was discovered that many variables had values different from the original data provided by the authors. In contrast to Schaeck et al. (2009), this analysis found that H-statistic was not statistically significant. However, there was a positive association between concentration and stability.

Thirdly, this chapter expanded the sample period of study. The original sample period of 1980-2005 was extended to 2011. The extension of the sample period raised a number of issues concerning whether to use constant or time-varying values for H-statistic and Concentration over the duration of the period. Schaeck et al. (2009) used constant values. A number of combinations of constant and time-varying values for the respective variables were estimated. H-statistic was consistently insignificant. Fourthly, an alternative measure of financial stability, Z-score, was employed. Neither H-statistic nor Concentration were statistically significant for this analysis.

The fifth step incorporated two alternative measures of competition, the Lerner index and the Boone indicator. The estimated results for these alternative competition variables were statistically insignificant in more than half the specifications. Finally, this chapter removed the effect of the global financial crisis and re-estimated the results. The competition measures continued to be statistically insignificant, though the concentration variable was found to be positively associated with stability.

The conclusion of this replication exercise is that it did not find evidence to support Schaeck et al.'s (2009) claim that competitive banking systems are more stable. It did, however, find some support for the assertion that concentration is positively associated with financial stability.

6.3 What is the Effect of Bank Competition on Financial Stability?

Chapters three and four addressed this question by performing Meta-Regression-Analysis (MRA). Chapter three is a replication of Zigraiova and Havranek (2016) meta-analysis on the effect of bank competition on stability. This chapter performed a pure replication using the authors' dataset and codes. A verification exercise examined 31 studies used by Zigraiova and Havranek (2016) and recoded the estimates, using the same categories that they used. Both exercises confirmed the conclusion of Zigraiova and Havranek (2016), that there is a small effect from bank competition on financial stability. Furthermore, it also confirmed that there is moderate publication bias, with journals favouring estimates supporting the bank competition and financial fragility hypothesis.

A large number of study and data characteristics are associated with the heterogeneity of estimates observed in the literature. This leads to uncertainty about which variable specification is most appropriate for relating characteristics to estimates. Bayesian Model Averaging was used to handle this “model uncertainty problem”. The associated results show that sample size, country coverage, measures for stability and competition, estimation method, and publication characteristics were the main contributory factors for heterogeneity.

Large samples generally produced small estimates of competition effects. The estimates for developed countries were slightly larger than those for developing and transition countries. Non-linear estimates were generally smaller when explanatory variables were weighted by the inverse number of estimates per study. Using a dummy variable to indicate a financial crisis generally produced larger estimates of the relationship between competition and stability than other measures of stability. With respect to competition measures, H-statistic was generally associated with larger estimated competition effects, and the Boone indicator with smaller estimated effects. Studies that used logit estimation produced smaller estimates than other studies. Number of citations, year the study first appeared in Google Scholar, the recursive impact factor, and whether a study was published in a peer-reviewed journal were all selected as important determinants of estimated competition effects.

Chapter four extended Zigraiova and Havranek (2016) work by updating the list of studies that estimated the relationship between bank competition and financial stability. This analysis found a total of 35 additional studies with 762 estimates. The exact same procedures employed by Zigraiova and Havranek (2016) were used to confirm whether their original findings would hold up with the new data. The associated partial correlation coefficients were usually less than -0.07 in absolute value, indicating a small negative effect from bank competition on financial stability. There was no statistical evidence in favour of publication bias. The meta-regression analysis identified country coverage, measures of stability and competition, estimation method, and publication characteristics as important factors when estimating the competition-stability relationship.

Overall, both chapters confirmed a small negative effect from bank competition on financial stability, with no evidence of publication bias in the more recent studies.

6.4 How Does Competition Affect Financial Stability?

Chapter five assessed this question. The previous two chapters revealed that the relationship between competition and stability varied due to country coverage, and the types of measures used to capture competition and stability, among other things. This chapter estimated the competition-stability relationship using US, bank-level data for the period 2000-2017. In light of findings from the previous chapters, this analysis used multiple proxies of competition and stability. Bank competition was measured by H-statistic, the Lerner index, and the Boone indicator. Bank-level stability was measured by Z-score, non-performing loans, and distance-to-default. Logistic R-squared and the change in conditional value at risk were used as measures of systemic stability.

This analysis found that the three measures of competition had low pairwise correlations and appeared to address different aspects of competition. The effect of competition on stability varied with the measure of stability. When Z-score was used as the stability measure, H-statistic, the Lerner index, and the Boone indicator found competition to be negatively associated with financial instability, supporting the competition-fragility hypothesis. Regressions with distance-to-default as the dependent variable also supported the competition-fragility hypothesis, however the associated estimated competition effects were generally insignificant.

However, other regressions produced inconsistent findings. When NPL was used as a measure of stability, regressions with H-statistic indicated a negative relationship between competition and stability. In contrast, both the Lerner index and the Boone indicator indicated a positive association. The results based on logistic R-squared and change in CoVaR were statistically insignificant. Therefore, the evidence for the final research question of the thesis is ambivalent. Most, but not all, of the empirical analysis indicates that competition is negatively associated with stability. Certainly, there is not much evidence to support the competition-stability hypothesis.

In summary, these findings suggest that competition in the banking sector does not have a large impact on financial stability. The main policy implication of the findings is that the relaxation of regulatory restrictions and the promotion of competition is unlikely to promote more stable outcomes in countries' financial systems.

References

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review, 106*(7), 1705-1741. doi:10.1257/aer.20120555

Agoraki, M.-E. K., Delis, M. D., & Pasiouras, F. (2011). Regulations, competition and bank risk-taking in transition countries. *Journal of Financial Stability, 7*(1), 38-48. doi:10.1016/j.jfs.2009.08.002

Akins, B., Li, L., Ng, J., & Rusticus, T. O. (2016). Bank Competition and Financial Stability: Evidence from the Financial Crisis. *Journal of Financial and Quantitative Analysis, 51*(01), 1-28. doi:10.1017/s0022109016000090

Ali, M. S. B. I., Timoumi and Zeitun Rami. (2015). Banking Concentration and Financial Stability: Evidence from Developed and Developing Countries. *Open Assessment E-Journal*(22).

Allen, F., & Gale, D. (2004). Competition and Financial Stability. *Journal of Money, Credit and Banking, 36*(3), 453-480.

Amidu, M. (2013). The effects of the structure of banking market and funding strategy on risk and return. *International Review of Financial Analysis, 28*, 143-155. doi:10.1016/j.irfa.2013.03.001

Amidu, M., & Wolfe, S. (2013). Does bank competition and diversification lead to greater stability? Evidence from emerging markets. *Review of Development Finance, 3*(3), 152-166. doi:10.1016/j.rdf.2013.08.002

Anginer, D., & Demirguc-Kunt, A. (2011). *Has the Global Banking System Become More Fragile over Time?* . Policy Research Working Paper, (5849).

Anginer, D., & Demirguc-Kunt, A. (2014). *Bank Capital and Systemic Stability* Policy Research Working Paper, (6948).

Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk? *Journal of Financial Intermediation, 23*(1), 1-26. doi:10.1016/j.jfi.2013.11.001

Angkinand, A. P., Sawangngoenyuang, W., & Wihlborg, C. (2010). Financial Liberalization and Banking Crises: A Cross-Country Analysis. *International Review of Finance, 10*(2), 263–292. doi:10.1111/j.1468-2443.2010.01114.x

Ashraf, D., Ramady, M., & Albinali, K. (2016). Financial fragility of banks, ownership structure and income diversification: Empirical evidence from the GCC region. *Research in International Business and Finance, 38*, 56-68. doi:10.1016/j.ribaf.2016.03.010

Barth, J. R., Caprio, G. J., & Levine, R. (2013). *Bank Regulation and Supervision in 180 Countries from 1999 to 2011*. NBER Working Paper Series, (18733).

Beck, T. (2008). *Bank Competition and Financial Stability: Friends or Foes?* World Bank Policy Research Working Paper (4656).

Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation, 22*(2), 218-244. doi:10.1016/j.jfi.2012.07.001

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2006). Bank concentration, competition, and crises: First results. *Journal of Banking & Finance, 30*(5), 1581-1603. doi:10.1016/j.jbankfin.2005.05.010

Berger, A. N., Demirgüç-Kunt, A., Levine, R., & Haubrich, J. G. (2004). Bank Concentration and Competition: An Evolution in the Making. *Journal of Money, Credit and Banking, 36*(3), 433-451.
Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research *European Journal of Operational Research, 98*, 175-212.
Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank Competition and Financial Stability. *Journal of Financial Services Research, 35*(2), 99-118. doi:10.1007/s10693-008-0050-7
Bharath, S. T., & Shumway, T. (2008). Forecasting Default with the Merton Distance to Default Model. *Review of Financial Studies, 21*(3), 1339-1369. doi:10.1093/rfs/hhn044
Bikker, J. A., & Haaf, K. (2002a). Competition, concentration and their relationship: An empirical analysis of the banking industry. *Journal of Banking and Finance, 26*, 2191-2214.
Bikker, J. A., & Haaf, K. (2002b). *Measures of Competition and Concentration in the Banking Industry: a Review of the Literature*. Research Series Supervision (discontinued)
Bikker, J. A., Shaffer, S., & Spierdijk, L. (2012). Assessing Competition with the Panzar-Rosse Model: The Role of Scale, Costs, and Equilibrium *The Review of Economics and Statistics, 94*(4), 1025-1044.
Bolt, W., & Humphrey, D. (2015). Assessing bank competition for consumer loans. *Journal of Banking & Finance, 61*, 127-141. doi:10.1016/j.jbankfin.2015.09.004
Boone, J. (2008). A New Way to Measure Competition. *The Economic Journal, 118*(531), 1245-1261.
Bordo, M. D., & Jeanne, O. (2002). *Boom-Busts in Asset Prices, Economic Instability, and Monetary Policy*. NBER Working Paper Series, (8966). Cambridge.
Boyd, J. H., & De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *Journal of Finance, 60*(3), 1329-1343. doi:DOI 10.1111/j.1540-6261.2005.00763.x
Boyd, J. H., De Nicolo, G., & Jalal, A. M. (2006). *Bank Risk-Taking and Competition Revisited: New Theory and New Evidence*. IMF Working Paper, (06/297).
Boyd, J. H., Graham, S. L., & Hewitt, S. R. (1993). Bank holding company mergers with nonbank financial firms: Effects on the risk of failure. *Journal of Banking and Finance, 17*, 43-63.
Boyd, J. H., & Runkle, D. E. (1993). Size and performance of banking firms *Journal of Monetary Economics, 31*, 47-67.
Bretschger, L., Kappel, V., & Werner, T. (2012). Market concentration and the likelihood of financial crises. *Journal of Banking & Finance, 36*(12), 3336-3345. doi:10.1016/j.jbankfin.2012.07.016
Bushman, R. M., Hendricks, B. E., & Williams, C. D. (2016). Bank Competition: Measurement, Decision-Making, and Risk-Taking. *Journal of Accounting Research, 54*(3), 777-826. doi:10.1111/1475-679x.12117
Calderon, C., & Schaeck, K. (2016). The Effects of Government Interventions in the Financial Sector on Banking Competition and the Evolution of Zombie Banks. *Journal of Financial and Quantitative Analysis, 51*(04), 1391-1436. doi:10.1017/s0022109016000478

Caminal, R., & Matutes, C. (2002). Market power and banking failures *International Journal of Industrial Organization, 20*, 1341-1361.

Caprio, G., & Klingebiel, D. (2002). *EPISODES OF SYSTEMIC AND BORDERLINE FINANCIAL CRISES*. World Bank Discussion Papers, (428). Washington D. C.

Casu, B., & Girardone, C. (2006). Bank Competition, Concentration and Efficiency in the Single European Market. *The Manchester School, 74*, 441-468.

Cerra, V., & Saxena, S. C. (2008). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review, 98*(1), 439-457. doi:10.1257/aer.98.1.439

Claessens, S., & Laeven, L. (2004). What Drives Bank Competition? Some International Evidence. *Journal of Money, Credit, and Banking, 36*(3), 563-583.

Cubillas, E., & González, F. (2014). Financial liberalization and bank risk-taking: International evidence. *Journal of Financial Stability, 11*, 32-48. doi:10.1016/j.jfs.2013.11.001

Curry, T., & Shibu, L. (2000). The Cost of the Savings and Loan Crisis: Truth and Consequences. *FDIC Banking Review, 13*, 26-35.

De Nicolo, G., & Loukoianova, E. (2007). *Bank Ownership, Market Structure and Risk*. IMF Working papers, (07/215).

Delis, M. D., & Kouretas, G. P. (2011). Interest rates and bank risk-taking. *Journal of Banking & Finance, 35*, 840–855.

Demirgüç-Kunt, A., & Detragiache, E. (1998). *The Determinants of Banking Crises in Developing and Developed Countries* Internationl Monetray Fund Staff Papers, (1, 45).

Demirgüç-Kunt, A., & Detragiache, E. (2002). Does deposit insurance increase banking system stability? An empirical investigation. *Journal of Monetary Economics, 49*, 1373-1406.

Demirgüç-Kunt, A., & Detragiache, E. (2005). Cross-Country Empirical Studies of Systemic Bank Distress: A Survey. *National Institute Economic Review, 192*, 68-83.

Demirguc-Kunt, A., Detragiache, E., & Gupta, P. (2000). *Inside the Crisis: An Empirical Analysis of Banking Systems in Distress*. Policy Research Working Paper, (2431).

Demirgüç-Kunt, A., Kane, E., & Laeven, L. (2014). *Deposit Insurance Database*. IMF Working Paper, (118).

Demirguc-Kunt, A., & Martinez-Peria, M. S. (2010). *A Framework for Analyzing Competition in the Banking Sector: An Application to the Case of Jordan*. Policy Research Working Paper, (5499).

Demsetz, R. S., & Strahan, P. E. (1997). Diversification, Size, and Risk at Bank Holding Companies. *Journal of Money, Credit and Banking, 29*(3), 300-313.

Diallo, B. (2015). Bank competition and crises revisited: New results. *Economics Letters, 129*, 81-86. doi:10.1016/j.econlet.2015.02.015

Doucouliagos, C. (2011). How large is large? Preliminary and relative guidelines for interpreting partial correlations in economics. *Economics Series, 2011/5*.

Doucouliagos, C., & Stanley, T. D. (2013). Are All Economic Facts Greatly Exaggerated? Theory Competition and Selectivity. *Journal of Economic Surveys, 27*(2), 316-339. doi:10.1111/j.1467-6419.2011.00706.x

Drees, B., & Pazarbasioglu, C. (1995). *The Nordic Banking Crises: Pitfalls in Financial Liberalization?* IMF Working Paper, (61). Washington, D. C.

Duygun, M., Shaban, M., & Weyman-Jones, T. (2015). Measuring competition using the Boone relative profit difference indicator. *Economics Letters, 132*, 117-120. doi:10.1016/j.econlet.2015.04.022

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in Meta-Analysis Detected by a Simple, Graphical Test. *British Medical Journal, 315*(7109), 629-634.

Eicher, T. S., Papageorgiou, C., & Raftery, A. E. (2011). Default priors and predictive performance in bayesian model averaging,with application to growth determinants. *Journal of Applied Econometrics, 26*(1), 30-55. doi:10.1002/jae.l

Fernández de Guevara, J., Maudos, J., & Pérez, F. (2007). Integration and competition in the European financial markets. *Journal of International Money and Finance, 26*(1), 26-45. doi:10.1016/j.jimonfin.2006.10.008

Fernandez, R. O., & Garza-Garciab, J. G. (2012). *The relationship between bank competition and financial stability: A case study of the Mexican banking industry*. Centre for Global Finance Working Paper, (03/12).

Fiordelisi, F., & Mare, D. S. (2014). Competition and financial stability in European cooperative banks. *Journal of International Money and Finance, 45*, 1-16. doi:10.1016/j.jimonfin.2014.02.008

Fu, X., Lin, Y., & Molyneux, P. (2014). Bank competition and financial stability in Asia Pacific. *Journal of Banking & Finance, 38*, 64-77. doi:10.1016/j.jbankfin.2013.09.012

Fungáčová, Z., & Weill, L. (2013). Does competition influence bank failures? *Economics of Transition, 21*(2), 301-322. doi:10.1111/ecot.12013

Furlong, F. T., & Keeley, M. C. (1989). Capital regulation and bank risk-taking: A note. *Journal of Banking & Finance, 13*(6), 883-891.

Giles, D. (2015). Correlation Isn't Necessarily Transitive. Retrieved from http://davegiles.blogspot.com/2015/12/correlation-isnt-necessarily-transitive.html

Goddard, J., & Wilson, J. O. S. (2009). Competition in banking: A disequilibrium approach. *Journal of Banking & Finance, 33*(12), 2282-2292. doi:10.1016/j.jbankfin.2009.06.003

Goetz, M. (2016). *Competition and Bank Stability*. CFS Working Paper, (559). Germany.

Halcoussis, D. (2005). *Understanding Econometrics*. Mason, Ohio Thomson/South-Western.

Hellmann, T. F., Murdock, K. C., & Stiglitz, J. E. (2000). Liberalization, Moral Hazard in Banking, and Prudential Regulation: Are Capital Requirements Enough? *The American Economic Review, 90*(1), 147-165.

Huljak, I. (2015). Market power and stability of CEE banks. *Business Systems Research Journal, 6*(2). doi:10.1515/bsrj-2015-0013

Hutchison, M. M., & Noy, I. (2005). How Bad Are Twins? Output Costs of Currency and Banking Crises *Journal of Money, Credit and Banking, 37*(4), 725-752.

Jeon, J. Q., & Lim, K. K. (2013). Bank competition and financial stability: A comparison of commercial banks and mutual savings banks in Korea. *Pacific-Basin Finance Journal, 25*, 253-272. doi:10.1016/j.pacfin.2013.10.003

Jiang, L., Levine, R., & Lin, C. (2017). *Does Competition affect bank risk?* NBER Working Paper Series.

Jiménez, G., Lopez, J. A., & Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability, 9*(2), 185-195. doi:10.1016/j.jfs.2013.02.004

Joyce, J. P., & Nabar, M. (2009). Sudden stops, banking crises and investment collapses in emerging markets. *Journal of Development Economics, 90*(2), 314-322. doi:10.1016/j.jdeveco.2008.04.004

Kaminsky, G. L., & Reinhart, C. M. (1999). The Twin Crises: The Causes of Banking and Balance-Of-Payments Problems. *American Economic Review, 89*(3), 473-500.

Karolyi, G. A., Lee, K.-H., & van Dijk, M. A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics, 105*(1), 82-112. doi:10.1016/j.jfineco.2011.12.008

Kasman, A., & Kasman, S. (2015). Bank size, competition and risk in the Turkish banking industry. *Empirica, 43*(3), 607-631. doi:10.1007/s10663-015-9307-1

Kasman, S., & Kasman, A. (2015). Bank competition, concentration and financial stability in the Turkish banking industry. *Economic Systems, 39*(3), 502-517. doi:10.1016/j.ecosys.2014.12.003

Keeley, M. C. (1990). Deposit Insurance, Risk, and Market Power in Banking. *The American Economic Review, 80*(5), 1183-1200.

Kick, T., & Prieto, E. (2015). Bank Risk and Competition: Evidence from Regional Banking Markets. *Review of Finance, 19*(3), 1185-1222. doi:10.1093/rof/rfu019

Kliestik, T., Misankova, M., & Kocisova, K. (2015). Calculation of Distance to Default. *Procedia Economics and Finance, 23*, 238-243. doi:10.1016/s2212-5671(15)00481-5

Laeven, L., & Valencia, F. (2008). *Systemic Banking Crises: A New Database* IMF Working Paper, (08/224).

Laeven, L., & Valencia, F. (2010). *Resolution of Banking Crises: The Good, the Bad, and the Ugly*. IMF Working Paper, (146).

Laeven, L., & Valencia, F. (2012). *Systemic Banking Crises Database : An Update*. IMF Working Paper, (12/163).

Leon, F. (2014). *Measuring competition in banking: A critical review of methods*. (12). France.

Leon, F. (2015). Does bank competition alleviate credit constraints in developing countries? *Journal of Banking & Finance, 57*, 130-142. doi:10.1016/j.jbankfin.2015.04.005

Lepetit, L., & Strobel, F. (2013). Bank insolvency risk and time-varying Z-score measures. *Journal of International Financial Markets, Institutions and Money, 25*, 73-87. doi:10.1016/j.intfin.2013.01.004

Leroy, A., & Lucotte, Y. (2017). Is there a competition-stability trade-off in European banking? *Journal of International Financial Markets, Institutions and Money, 46*, 199-215. doi:10.1016/j.intfin.2016.08.009

Levine, R. (2001). International Financial Liberalization and Economic Growth. *Review of International Economics, 9*(4), 688-702.

Liu, H., Molyneux, P., & Wilson, J. O. S. (2013). Competition and Stability in European Banking: A Regional Analysis. *The Manchester School, 81*(2), 176-201. doi:10.1111/j.1467-9957.2011.02285.x

Liu, H., & Wilson, J. O. S. (2013). Competition and risk in Japanese banking. *The European Journal of Finance, 19*(1), 1-18. doi:10.1080/1351847x.2011.633614

Mansournia, M. A., & Altman, D. G. (2016). Inverse probability weighting. *BMJ, 352*, i189. doi:10.1136/bmj.i189

Marcus, A. J. (1984). Deregulation and bank financial policy. *Journal of Banking & Finance, 8*(4), 557-565.

Matthews, K., Murinde, V., & Zhao, T. (2007). Competitive conditions among the major British banks. *Journal of Banking & Finance, 31*(7), 2025-2042. doi:10.1016/j.jbankfin.2006.11.009

Maudos, J., & Solís, L. (2011). Deregulation, liberalization and consolidation of the Mexican banking system: Effects on competition. *Journal of International Money and Finance, 30*(2), 337-353. doi:10.1016/j.jimonfin.2010.07.006

Merton, R. C. (1974). On The Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance, 29*(2), 449-470

Minsky, H. P. (1992). *The Financial Instability Hypothesis*. Handbook of Radical Political Economy. The Jerome Levy Economics Institute of Bard College.

Mishkin, F. S. (1999). Lessons from the Tequila Crisis. *Journal of Banking & Finance, 23*, 1521 - 1533.

Mishkin, F. S. (2006). How Big a Problem is Too Big to Fail? A Review of Gary Stern and Ron Feldman's Too Big to Fail: The Hazards of Bank Bailouts. *Journal of Economic Literature, 44*, 988–1004.

Molyneux, P., Lloyd-Williams, D. M., & Thornton, J. (1994). Competitive Conditions in European Banking. *Journal of Banking and Finance, 18*(3), 445-459.

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics, 58*, 215-260.

Mulder, C., Perrelli, R., & Rocha, M. D. (2012). External vulnerability, balance sheet effects, and the institutional framework — Lessons from the Asian crisis. *International Review of Economics and Finance, 21*, 16-28.

Noy, I. (2004). Financial liberalization, prudential supervision, and the onset of banking crises. *Emerging Markets Review, 5*, 341 - 359.

Oliver, A. M., Fumás, V. S., & Saurina, J. (2006). Risk premium and market power in credit markets. *Economics Letters, 93*(3), 450-456. doi:10.1016/j.econlet.2006.06.021

Olszak, M., S´witala, F., & Kowalska, I. (2013). *Competition in commercial banks in Poland – Analysis of Panzar-Rosse H-statistics*. Faculty of Management Working Paper Series, (4). Poland.

Panzar, J. C., & Rosse, J. N. (1987). Testing For "Monopoly" Equilibrium *The Journal of Industrial Economics, 35*(4), 443-456.

Papke, L. E., & Wooldridge, J. M. (1996). Econometric Methods for Fractional Response Variables with an Application to 401 (K) Plan Participation Rates. *Journal_of_Applied_Econometrics., 11*, 619-632.

Pawlowska, M. (2012). *Competition, concentration and foreign capital in the Polish banking sector (prior and during the financial crisis)*. National Bank of Poland Working Papers (130).

Ranciere, R., Tornell, A., & Westermann, F. (2006). Decomposing the effects of financial liberalization: Crises vs. growth. *Journal of Banking & Finance, 30*(12), 3331-3348. doi:10.1016/j.jbankfin.2006.05.019

Reinhart, C. M., & Rogof, K. S. (2013). Banking crises: An equal opportunity menace. *Journal of Banking and Finance, 37*, 4557– 4573. doi:10.1016/j.jbankfin.2013.03.005

Reinhart, C. M., & Rogoff, K. S. (2008). Is the 2007 US Sub-Prime Financial Crisis so Different? An International HistoricalComparison. *American Economic Review, 98*(2), 339-344.

Schaeck, K., & Cihak, M. (2008). *How does competition affect efficiency and soundness in banking? New empirical evidence*. Working Paper Series, (932).

Schaeck, K., & Cihak, M. (2010). *Competition, Efficiency, and Soundness in Banking: An Industrial Organization Perspective*. European Banking Center Discussion Paper (2010-20S).

Schaeck, K., & Cihak, M. (2014). Competition, Efficiency, and Stability in Banking. *Financial Management, 43*, 215 - 241.

Schaeck, K., Cihak, M., & Wolfe, S. (2009). Are Competitive Banking Systems More Stable? *Journal of Money, Credit and Banking, 41*(4), 711-734.

Shaffer, S., & Spierdijk, L. (2015). The Panzar–Rosse revenue test and market power in banking. *Journal of Banking & Finance, 61*, 340-347. doi:10.1016/j.jbankfin.2015.09.019

Soedarmono, W., Machrouh, F., & Tarazi, A. (2013). Bank competition, crisis and risk taking: Evidence from emerging markets in Asia. *Journal of International Financial Markets, Institutions and Money, 23*, 196-221. doi:10.1016/j.intfin.2012.09.009

Spierdijk, L., & Zaouras, M. (2016). The Lerner index and revenue maximization. *Applied Economics Letters, 24*(15), 1075-1079. doi:10.1080/13504851.2016.1254333

Stanley, T. D. (2007). Meta-Regression Methods for Detecting and Estimating Empirical Effects in the Presence of Publication Selection. *Oxford Bulletin of Economics and Statistics, 0*(0), 070921170652004-??? doi:10.1111/j.1468-0084.2007.00487.x

Tabak, B. M., Fazio, D. M., & Cajueiro, D. O. (2012). The relationship between banking market competition and risk-taking: Do size and capitalization matter? *Journal of Banking & Finance, 36*(12), 3366-3381. doi:10.1016/j.jbankfin.2012.07.022

Tabak, B. M., Gomes, G. M. R., & da Silva Medeiros, M. (2015). The impact of market power at bank level in risk-taking: The Brazilian case. *International Review of Financial Analysis, 40*, 154-165. doi:10.1016/j.irfa.2015.05.014

Tang, H., Zoli, E., & Klytchnikova, I. (2000). *Banking Crises in Transition Countries: Fiscal Costs and Related Issues*. Policy Research Working Paper, (WPS2484).

The World Bank. (2016). Financial stability. Retrieved from http://www.worldbank.org/en/publication/gfdr/gfdr-2016/background/financial-stability

Turk-Ariss, R. (2010). On the implications of market power in banking: Evidence from developing countries. *Journal of Banking & Finance, 34*(4), 765-775. doi:10.1016/j.jbankfin.2009.09.004

Uhde, A., & Heimeshoff, U. (2009). Consolidation in banking and financial stability in Europe: Empirical evidence. *Journal of Banking & Finance, 33*(7), 1299-1311. doi:10.1016/j.jbankfin.2009.01.006

Van-Bergeijk, P. A. G. (2016). What a Difference a Data Version Makes. Retrieved from https://replicationnetwork.com/2016/11/29/van-bergeijk-what-a-difference-a-data-version-makes/

van Leuvensteijn, M., Bikker, J. A., van Rixtel, A. A. R. J. M., & Sørensen, C. K. (2011). A new approach to measuring competition in the loan markets of the euro area. *Applied Economics, 43*(23), 3155-3167. doi:10.1080/00036840903493234

Vives, X. (2001). Competition in the Changing World of Banking. *Oxford Review of Economic Policy, 17*(4), 535-547.

Wooldridge, J. M. (2013). *Introductory Econometrics A Modern Approach* (5th Edition ed.). USA: South-Western Cengage Learning.

Yeyati, E. L., & Micco, A. (2007). Concentration and foreign penetration in Latin American banking sectors: Impact on competition and risk. *Journal of Banking & Finance, 31*(6), 1633-1647. doi:10.1016/j.jbankfin.2006.11.003

Zeugner, S., & Feldkircher, M. (2015). Bayesian Model Averaging Employing Fixed and Flexible Priors: TheBMSPackage forR. *Journal of Statistical Software, 68*(4). doi:10.18637/jss.v068.i04

Zigraiova, D., & Havranek, T. (2016). Bank Competition and Financial Stability: Much Ado About Nothing? *Journal of Economic Surveys, 30*(5), 944-981. doi:10.1111/joes.12131

Appendices

Appendix 1

Description of Variables and Data Sources

Variable	Definition	Data Sources
GDP growth (lag)	Rate of growth of the gross domestic production (GDP) lagged by one year	World Bank Development Indicators*, International financial Statistics
Inflation	Rate of change of the GDP deflator	World Bank Development Indicators*, International financial Statistics
Real interest rate	Inflation adjusted rate of inflation	World Bank Development Indicators, Datamarket
Depreciation	Change in the foreign exchange rate	International financial Statistics*, World Bank Development Indicators
Terms of trade	Change in the net barter terms of trade	DataMarket, World Bank Development Indicators*
Credit growth	Rate of growth of domestic credit to the private sector, adjusted for inflation with GDP deflator	World Bank Development Indicators, Global Financial Development Database
Moral hazard index	Indicator of generosity of design features of deposit insurance schemes. It is calculated as the first principal component of the following design features: no co-insurance, unlimited explicit coverage, explicit coverage limit, coverage of foreign currency and interbank deposits (Demirgüç-Kunt & Detragiache, 2002)	Demirgüç-Kunt et al. (2014) Deposit Insurance Database
German legal origin	Dummy variable that takes the value one if the country's legal system is of German origin or zero otherwise	Schaeck et al. (2009) (same data collects from the original paper)
Scandinavian legal origin	Dummy variable that takes the value one if the country's legal system is of Scandinavian origin or zero otherwise	Schaeck et al. (2009) (same data collects from the original paper)

Variable	Definition	Data Sources
British legal origin	Dummy variable that takes the value one if the country's legal system is of British origin or zero otherwise	Schaeck et al. (2009) (same data collects from the original paper)
Concentration	Percentage of total assets held by the three largest institutions in a country (averaged over the sampling period)	Schaeck et al. (2009) (same data collects from the original paper) and Global Financial Development Database
H-statistic (H1)	H1 is calculated as the average of four models estimated for each country for the period 1998–2005 based on Section2.4.1, whereby two models employ OLS with time dummies and GLS with fixed bank effects and time dummies	Schaeck et al. (2009) (same data from the original paper) and Global Financial Development Database
Private credit/GDP	Private credit by deposit money banks as a percentage of GDP	World Bank Development Indicators
Foreign ownership	Proportion of bank assets owned by foreign entities in a country	Barth, Caprio, and Levine (2013)
Government ownership	Proportion of bank assets owned by government banks in a country	Barth et al. (2013)
Entry restrictions	The indicator is constructed as an index and it takes on values between 1 and 8, whereby a higher index value indicates greater entry restrictions	Barth et al. (2013)
Capital regulatory index	An index of the stringency of bank capital regulations	Barth et al. (2013)
Official supervisory power	A measure of the degree to which the country's bank supervisory body to take actions to prevent banking problems	Barth et al. (2013)

Variable	Definition	Data Sources
Private monitoring index	This index contains information regarding external auditing of banks, which proportion of banks is rated by international agencies, if an explicit deposit insurance scheme is present, whether subordinated debt is allowed as a part of capital, and if risk management procedures and off-balance sheet items are disclosed to the public. it takes values between 0 and 12, where a larger value indicates greater degree of private monitoring	Barth et al. (2013)
Z-score	It measures the probability of default of a country's banking system. Z-score compares capitalization and returns with the volatility of those returns.	Global Financial Development Database
Lerner index	This is a measure of market power of the bank. It is the difference between output prices and marginal costs. Prices are calculated as total bank revenue over assets, whereas marginal costs are calculated from a translog cost function with respect to output costs. Higher values of the Lerner index indicate less bank competition. This database uses the methodology of Demirgüç-Kunt and Martínez Pería (2010) to calculate the country-level Lerner index	Global Financial Development Database

Variable	Definition	Data Sources
Boone indicator	This is a measure of degree of competition, calculated as the elasticity of profits to marginal costs. To estimate the elasticity, the log of profits is regressed on the log of average costs. The estimated coefficient is the Boone indicator. According to the interpretation of the Boone indicator, higher profits are achieved by more-efficient banks. Hence, the more negative the Boone indicator, the higher the degree of competition. This database uses the methodology of Schaeck and Cihák (2010) to calculate the country-level Boone indicator	Global Financial Development Database

Note. An asterisk indicates that the respective data source was used by Schaeck et al. (2009).

Appendix 2

Description of Variables

Variable	Description
Data characteristics	
PCC	The transformed coefficient estimate of the effect of bank competition on financial stability
SEPCC	The estimated standard error of the partial correlation coefficient
Samplesize	The logarithm of the number of observations used in the competition-stability regression
T	The logarithm value of the number of time periods (years)
Sampleyear	The mean year of the sample period (base year:1992)
Countries examined	
Developed	Equals 1 if primary studies examine only OECD countries
Developing and transition	Equals 1 if primary studies examine only non-OECD countries
Reference case: mixed	Equals 1 if primary studies examine both OECD and non-OECD countries
Design of the analysis	
Quadratic	Equals 1 if squared term of the competition coefficient is included in the competition-stability regression
Endogeneity	Equals 1 if the estimation method includes an instrument, a lagged value of competition, or a dummy variable to account for endogeneity
Macro	Equals 1 if the competition-stability regression is estimated based on aggregated country-level data
Averaged	Equals 1 if the competition-stability regression is estimated based on the country-level data, which are calculated as the average of bank-level data
Treatment of stability	
Dummies	Equals 1 if proxy measure of stability is a dummy variable for bank crisis
NPL	Equals 1 if proxy measure of stability is the ratio of nonperforming loans

Variable	Description
Z_score	Equals 1 if proxy measure of stability is Z-score
Profit volatility	Equals 1 if proxy measure of stability is ROA volatility /ROE volatility
Profitability	Equals 1 if proxy measure of stability is ROA/ROE
Capitalization	Equals 1 if proxy measure of stability is Capital Adequacy (CAR)/Equity to total assets
DtoD	Equals 1 if proxy measure of stability is Logistic R^2, Distance-to-default, or probability of bankruptcy
Reference case: other_stability	Equals 1 if any other measure of stability is used by primary studies
Treatment of competition	
H-statistic	Equals 1 if bank competition is measured using the H-statistic
Boone	Equals 1 if bank competition is measured using the Boone indicator
Concentration	Equals 1 if bank competition is measured using a three bank or five bank concentration ratio
Lerner	Equals 1 if bank competition is measured using the Lerner index
HHI	Equals 1 if bank competition is measured using the Herfindahl-Hirschman index
Reference case:	Equals 1 if any other measure of competition is used by primary studies
Estimation method	
Logit	Equals 1 if Logit or Probit model is used to estimate the competition-stability regression
OLS	Equals 1 if OLS is used to estimate the competition-stability regression
FE	Equals 1 if fixed effects are used to estimate the competition-stability regression
RE	Equals 1 if random effects are used to estimate the competition-stability regression
GMM	Equals 1 if GMM is used to estimate the competition-stability regression

Variable	Description
TSLS	Equals 1 if two-stage least squares are used to estimate the competition-stability regression
Reference case:	Equals 1 if any other estimation method is used to estimate the competition-stability regression
Control variables	
Regulation	Equals 1 if regulatory or supervisory variables are included in the estimation equation
Ownership	Equals 1 if bank ownership variables are included in the estimation equation
Global	Equals 1 if macroeconomic variables are included in the estimation equation
Publication characteristics	
Citations	The logarithm of the number of Google Scholar citations normalized by the difference between 2015 and the year the study is first appeared in Google Scholar (collected in July 2014 by Z&H)
Firstpub	The year when the study is first appeared in Google Scholar (base year: 2003)
IFrecursive	The recursive impact factor values from RePEc (collected in July 2014 by Z&H)
Reviewed journal	Equals 1 if the study is published in a peer-reviewed journal

Appendix 3

Description of Variables

Variable	Description
Data characteristics	
PCC	The transformed coefficient estimate of the effect of bank competition on financial stability
SEPCC	The estimated standard error of the partial correlation coefficient
Samplesize	The logarithm of the number of observations used in the competition-stability regression
T	The logarithm value of the number of time periods (years)
Sampleyear	The mean year of the sample period (base year:1992)
Countries examined	
Developed	Equals 1 if primary studies examine only OECD countries
Developing and transition	Equals 1 if primary studies examine only non-OECD countries
Reference case: mixed	Equals 1 if primary studies examine both OECD and non-OECD countries
Design of the analysis	
Quadratic	Equals 1 if squared term of the competition coefficient is included in the competition-stability regression
Endogeneity	Equals 1 if the estimation method includes an instrument, a lagged value of competition, or a dummy variable to account for endogeneity
Macro	Equals 1 if the competition-stability regression is estimated based on aggregated country-level data
Averaged	Equals 1 if the competition-stability regression is estimated based on the country-level data, which are calculated as the average of bank-level data
Treatment of stability	
Dummies	Equals 1 if proxy measure of stability is a dummy variable for bank crisis
NPL	Equals 1 if proxy measure of stability is the ratio of nonperforming loans

Variable	Description
Z_score	Equals 1 if proxy measure of stability is Z-score
Profit volatility	Equals 1 if proxy measure of stability is ROA volatility /ROE volatility
Profitability	Equals 1 if proxy measure of stability is ROA/ROE
Capitalization	Equals 1 if proxy measure of stability is Capital Adequacy (CAR)/Equity to total assets
DtoD	Equals 1 if proxy measure of stability is Logistic R^2, Distance-to-default, or probability of bankruptcy
Reference case: other_stability	Equals 1 if any other measure of stability is used by primary studies
Treatment of competition	
H-statistic	Equals 1 if bank competition is measured using the H-statistic
Boone	Equals 1 if bank competition is measured using the Boone indicator
Concentration	Equals 1 if bank competition is measured using a three bank or five bank concentration ratio
Lerner	Equals 1 if bank competition is measured using the Lerner index
HHI	Equals 1 if bank competition is measured using the Herfindahl-Hirschman index
Reference case:	Equals 1 if any other measure of competition is used by primary studies
Estimation method	
Logit	Equals 1 if Logit or Probit model is used to estimate the competition-stability regression
OLS	Equals 1 if OLS is used to estimate the competition-stability regression
FE	Equals 1 if fixed effects are used to estimate the competition-stability regression
RE	Equals 1 if random effects are used to estimate the competition-stability regression
GMM	Equals 1 if GMM is used to estimate the competition-stability regression

Variable	Description
TSLS	Equals 1 if two-stage least squares are used to estimate the competition-stability regression
Reference case:	Equals 1 if any other estimation method is used to estimate the competition-stability regression
Control variables	
Regulation	Equals 1 if regulatory or supervisory variables are included in the estimation equation
Ownership	Equals 1 if bank ownership variables are included in the estimation equation
Global	Equals 1 if macroeconomic variables are included in the estimation equation
Publication characteristics	
Citations	The logarithm of the number of Google Scholar citations normalized by the difference between 2017 and the year the study is first appeared in Google Scholar (collected in June 2017 by Z&H)
Firstpub	The year when the study is first appeared in Google Scholar (base year: 2003)
IFrecursive	The recursive impact factor values from RePEc (collected in June 2017)
Reviewed journal	Equals 1 if the study is published in a peer-reviewed journal

Appendix 4

A List of Additional Papers on Bank Competition and Financial Stability

Ak Kocabay, S. (2009). *Bank Competition and Banking System Stability: Evidence from Turkey*. Middle East Technical University, Turkey The Graduate School of Social Sciences

Akins, B., Li, L., Ng, J., & Rusticus, T. O. (2016). Bank Competition and Financial Stability: Evidence from the Financial Crisis. *Journal of Financial and Quantitative Analysis, 51*(01), 1-28. doi: 10.1017/s0022109016000090

Ali, M. S. B., Intissar, T., & Zeitun, R. (2016). Banking Concentration and Financial Stability. New Evidence from Developed and Developing Countries. *Eastern Economic Journal, 44*(1), 117-134. doi: 10.1057/eej.2016.8

Amidu, M. (2013). The effects of the structure of banking market and funding strategy on risk and return. *International Review of Financial Analysis, 28,* 143-155. doi: 10.1016/j.irfa.2013.03.001

Amidu, M., & Wolfe, S. (2013). Does bank competition and diversification lead to greater stability? Evidence from emerging markets. *Review of Development Finance, 3*(3), 152-166. doi: 10.1016/j.rdf.2013.08.002

Ashraf, D., Ramady, M., & Albinali, K. (2016). Financial fragility of banks, ownership structure and income diversification: Empirical evidence from the GCC region. *Research in International Business and Finance, 38,* 56-68. doi: 10.1016/j.ribaf.2016.03.010

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2003). *Bank Concentration and Crises* NBER Working Paper Series (9921).

Bretschger, L., Kappel, V., & Werner, T. (2012). Market concentration and the likelihood of financial crises. *Journal of Banking & Finance, 36*(12), 3336-3345. doi: 10.1016/j.jbankfin.2012.07.016

Bushman, R. M., Hendricks, B. E., & Williams, C. D. (2016). Bank Competition: Measurement, Decision-Making, and Risk-Taking. *Journal of Accounting Research, 54*(3), 777-826. doi: 10.1111/1475-679x.12117

Diallo, B. (2015). Bank competition and crises revisited: New results. *Economics Letters, 129,* 81-86. doi: 10.1016/j.econlet.2015.02.015

Dushku, E. (2016). Bank risk-taking and competition in the Albanian banking sector. *South-Eastern Europe Journal of Economics 2*, 187-203.

Fiordelisi, F., & Mare, D. S. (2014). Competition and financial stability in European cooperative banks. *Journal of International Money and Finance, 45,* 1-16. doi: 10.1016/j.jimonfin.2014.02.008

Fungáčová, Z., & Weill, L. (2013). Does competition influence bank failures? *Economics of Transition, 21*(2), 301-322. doi: 10.1111/ecot.12013

Goetz, M. (2016). *Competition and Bank Stability*. CFS Working Paper, (559). Germany.

Huljak, I. (2015). Market power and stability of CEE banks. *Business Systems Research Journal, 6*(2). doi: 10.1515/bsrj-2015-0013

Jiang, L., Levine, R., & Lin, C. (2017). *Does Competition affect bank risk?* NBER Working Paper Series.

Jiménez, G., Lopez, J. A., & Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability, 9*(2), 185-195. doi: 10.1016/j.jfs.2013.02.004

Kasman, A., & Kasman, S. (2015). Bank size, competition and risk in the Turkish banking industry. *Empirica, 43*(3), 607-631. doi: 10.1007/s10663-015-9307-1

Kasman, S., & Kasman, A. (2015). Bank competition, concentration and financial stability in the Turkish banking industry. *Economic Systems, 39*(3), 502-517. doi: 10.1016/j.ecosys.2014.12.003

Kick, T., & Prieto, E. (2015). Bank Risk and Competition: Evidence from Regional Banking Markets. *Review of Finance, 19*(3), 1185-1222. doi: 10.1093/rof/rfu019

Labidi, W., & Mensi, S. (2015). *Does banking market power matter on financial (in)stability? Evidence from the banking industry MENA region*. Working Paper Series, (908). University of Manouba.

Leroy, A., & Lucotte, Y. (2017). Is there a competition-stability trade-off in European banking? *Journal of International Financial Markets, Institutions and Money, 46*, 199-215. doi: 10.1016/j.intfin.2016.08.009

Mirzaei, A., Moore, T., & Liu, G. (2013). Does market structure matter on banks' profitability and stability? Emerging vs. advanced economies. *Journal of Banking & Finance, 37*(8), 2920-2937. doi: 10.1016/j.jbankfin.2013.04.031

Okumus, H. S., & Kibritciartar, O. (2012). Islamic Banks And Financial Stability in the GCC: An Empirical Analysis. *Istanbul Commerce University Journal of Social Sciences 11*(21), 147-164.

Pak, O., & Nurmakhanova, M. (2013). The Effect of Market Power on Bank Credit Risk-Taking and Bank Stability in Kazakhstan. *Transition Studies Review, 20*(3), 335-350. doi: 10.1007/s11300-013-0297-z

Pawlowska, M. (2016). Does the size and market structure of the banking sector have an effect on the financial stability of the European Union? *The Journal of Economic Asymmetries, 14*, 112-127. doi: 10.1016/j.jeca.2016.07.009

Pino, G., & Araya, I. (2013). Impact of the Heterogeneity in Market Power on the Relationship Between Risk Taking and Competition: Case of the Chilean Banking Sector. *Emerging Markets Finance and Trade, 49*(4), 98-112. doi: 10.2753/ree1540-496x490405

Ruiz-Porras, A. (2008). *Banking Competition and Financial Fragility: Evidence from Panel-Data*. Economic Studies, (23, 1).

Sarkar, S., & Sensarma, R. (2016). The relationship between competition and risk-taking behaviour of Indian banks. *Journal of Financial Economic Policy, 8*(1), 95-119. doi: 10.1108/jfep-05-2015-0030

Sinha, P., & Sharma, S. (2016). *Relationship of Financial Stability and Risk with Market Structure and Competition: Evidence from Indian Banking Sector*. Munich Personal RePEc Archive, (72247). Germany

Soedarmono, W., Machrouh, F., & Tarazi, A. (2011). Bank market power, economic growth and financial stability: Evidence from Asian banks. *Journal of Asian Economics, 22*(6), 460-470. doi: 10.1016/j.asieco.2011.08.003

Soedarmono, W., & Tarazi, A. (2016). Competition, Financial Intermediation, and Riskiness of Banks: Evidence from the Asia-Pacific Region. *Emerging Markets Finance and Trade, 52*(4), 961-974. doi: 10.1080/1540496x.2015.1018039

Tan, Y., & Floros, C. (2014). Risk, Profitability, and Competition: Evidence from the Chinese Banking Industry. *The Journal of Developing Areas, 48*(3), 303-319. doi: 10.1353/jda.2014.0054

Troug, H. A., & Sbia, R. (2015). The Relationship between Banking Competition and Stability in Developing Countries: The Case of Libya. *International Journal of Economics and Financial Issues 5*(3), 772-779.

Wang, X., Zeng, X., & Zhang, Z. (2014). The influence of the market power of Chinese commercial banks on efficiency and stability. *China Finance Review International, 4*(4), 307-325. doi: 10.1108/cfri-07-2013-0096

Appendix 5

A list of countries included in Schaeck et al. (2009)

1. Argentina
2. Austria
3. Bahrain
4. Bangladesh
5. Belgium
6. Brazil
7. Canada
8. Chile
9. Colombia
10. Costa Rica
11. Cyprus
12. Denmark
13. Dominican Republic
14. France
15. Germany
16. Greece
17. Hong Kong
18. India
19. Indonesia
20. Ireland
21. Israel
22. Italy
23. Japan
24. Kenya
25. Malaysia
26. Netherlands
27. Nigeria
28. Norway
29. Pakistan
30. Paraguay
31. Panama
32. Peru
33. Philippines
34. Portugal
35. Saudi Arabia
36. Senegal
37. South Africa
38. Sweden
39. Switzerland
40. Thailand
41. Tunisia
42. Turkey
43. United Kingdom
44. United States
45. Venezuela